Impossible Probability:

Anthology,

Vol 3.

I doubt, therefore I exist.

Dr Ruben Garcia Pedraza

Preliminary Words for the Publication of *Impossible Probability, Anthology*, in Spanish:

Impossible Probability

The work presented here is a compilation of the posts I published on the blog *Impossible Probability* between 1 August 2011 and 13 January 2018, the posts I wrote in Spanish. From 13 January onwards, while living and working in London in different schools, and given the importance we already knew Global Artificial Intelligence was going to have, I would try to write them in English with the help of online correctors and translators, especially Google, and later I would use Grammarly.

The originals written in English, with all their imperfections, are still preserved on the *Impossible Probability* blog, and also on Internet Archive, where my poetic works can also be found.

As I have said on numerous occasions, especially in my poetry, behind every imperfection, behind every subtlety, entire hidden worlds are concealed, full of mystery and uncertainty yet to be discovered, and that the adventurous and hungry mind can find as easily as going to Internet Archive, where all my secrets await the right reader who knows how to translate them—like someone who by mistake finds a secret entrance, the passage leading to the cave where the elves who guard hidden knowledge dwell, and the dragons who defend the golden fortress.

While the original texts in English can be found on Internet Archive, the corrected and expanded version, this time using ChatGPT, can be found in scientific repositories (Zenodo, ORCID, PhilPapers) and on Amazon. In any case, if in the future a comparative study were carried out between my original texts in the *Impossible Probability* blog and Internet Archive, and the corrected and expanded versions, it would be clear without

any difficulty that the original contents are perfectly preserved, and the corrected and expanded versions are faithful to the contents we wrote together in 2018 in relation to Gaia, Mother, the Global Artificial Intelligence.

The importance of the documents that in this new series of books *Impossible Probability: Anthology* will be published in Spanish, containing the articles between 1 August 2011 and 13 January 2018, lies in the fact that we began to write this blog just a few weeks before the death of José Rodríguez Delgado, and a few months before the publication of our book *Introduction to Impossible Probability, Statistics of Probability and Statistical Probability.*

Although it is very difficult at the moment to explain who "we" are, and what *Impossible Probability* means for us, what matters is the work we leave: our work, our legacy, our *legend*, *our symbol*, our seal—independently of the judgment that history may later make of our contribution to the development of mathematics, Artificial Intelligence, and most importantly, Cyborg Psychology.

The first time we began to write about *Impossible Probability* I was only a student in the Faculty of Education at the Complutense University of Madrid [the Dean was Gonzalo Vazquez]. In my first year of university I had as professor Jesús Martín Ramírez, collaborator of Karl Pribram and author of the brain hologram theory, which is the origin of cyborg psychology. While José Delgado provided the structure, the stimoceiver, nevertheless, to understand the functioning of this technology in the 1970s and 80s, Pribram's contribution was fundamental—and even today it still is.

My first year of university was fabulous: good grades, good vacations hiking, summer camps in the mountains of Madrid—and suddenly, in the second year of university 1996–1997, my life would change abruptly, which can be seen in my poetry, how my poems began to acquire a more dramatic tone.

I repeated statistics in my second year, I repeated it at least three years, and I was even on the verge of being expelled from university. Miraculously, it did not happen, and precisely the last year I had left to pass statistics, I passed. The following year I would begin to write *Impossible Probability* as a critique of Karl Popper—and in a certain sense, it is.

Whereas for Karl Popper knowledge is false, only accepted provisionally as true until we refute it, in *Impossible Probability* rational knowledge is provisionally true while we investigate true pure knowledge—in the ultimate instance, our search for knowledge of the noumenon, which the human being cannot reach, hence the necessity of Global Artificial Intelligence: that machine capable of knowing what happens beyond human limitations.

What we call chaos, error, complexity, is only the noise produced by our human cognitive limitations, given our apriorism. The human being, limited both sensorially and cognitively, cannot know what really happens, but we can build the machine that can reach true knowledge of what happens—the truth in itself and for itself. That is, and no other, the true end of Artificial Intelligence: to reach the knowledge of truth, whatever it may be.

The path that takes me from my first works in *Impossible Probability* to Global Artificial Intelligence is not easy: much suffering, even despair, sometimes a sense of helplessness, a sense of abandonment—yet an inner force always pushed me forward. That inner force is what I call "we," although I understand that at this moment it is inexplicable.

Although I feel a bond that unites me to the *legend* of José Rodríguez Delgado, and which my Stockholm syndrome prevents me from understanding, my bond with Pribram is evident: Jesús Martín Ramírez. Pribram and Delgado worked at Yale University; probably only the skulls can say whether both were members of Skull & Bones, though there is no evidence to corroborate this.

Impossible Probability is a work that comes out of the romanticism of a student poet, who believed in white fairies, the rays of Zeus, and the light of the god Apollo illuminating the heart of every spirit and soul in a world full of mysteries and shadows.

It was from that world of poetry, in a country emerging from a failed transition, that the last survivor of the dream of reason would listen to his inner voice, dark and serene, and *Impossible Probability* would be born for the first time.

The first formulations of *Impossible Probability* date from 11 September 2001. My first formula would be the Impact of the Defect; then on 16 October 2002 the Second Method would appear, laying the foundations of the distinction between empirical and theoretical probability. I worked intensely until 2004. Between 2004 and 19 December 2009, I paused my mathematical frenzy, and it was not until 19 December 2009 when I returned, this time with the intention of publishing *Introduction to Impossible Probability, Statistics of Probability or Statistical Probability*, whose publication materialized just a few months after the death of José Rodríguez Delgado, although Delgado was able to see the first works published online in this *Impossible Probability* blog, which makes this blog a fundamental piece for understanding our work, our legacy, and most importantly—independently of our names, which matter little—the truly essential: our seed of the future, our eternal gratitude, a work of intelligence that will lay the foundations of the future technological society.

Dr. Rubén García Pedraza

20 August 2025, 19:00

Madrid, Villaverde

Preliminary Words for the English Version of *Impossible Probability, Anthology*.

Spanish-speaking readers have been able to enjoy our work since we began the foundational work of *Impossible Probability* in 2001, more precisely when we began to make it public in July 2011 through the *Impossible Probability* blog. The work presented here is an extended version of the posts published on the blog, an extended version translated into English with the help of Gepeto, my special GPT program.

In any case, a comparative study of the augmented translation presented here and the original works in Spanish could corroborate that the essential contents related to formulation and the philosophy of mathematics remain in accordance with the original electrical spirit of *Impossible Probability*.

The reason that obliges me to publish so hastily the English-language publication of all my works is the very complicated personal situation in which I find myself, due to serious mistakes committed by certain British institutions, which, completely blind to what our situation is, instead of having supported our program from the first moment, tried to sabotage it from the beginning through numerous obstacles and false loves.

I have no doubt that the manipulation to which I have been subjected by British institutions will one day be investigated, and at some point justice must make an appearance.

When that day comes, the first thing justice must recognize is the extreme difficulty and harshness of the conditions I have lived all my life since my earliest childhood. From the very day I came out of my mother's womb in Spain I have known nothing but pain and the oblivion of a society that prefers to look the other way and wash its hands, pretending that nothing is happening here. In the midst of the dictatorship of silence, I have had to survive all kinds of traps, deceptions, and attempts at assassination. The dictatorship of silence, the Roman circus, and the virtual zoo that my life has become will one day have to end. For this reason I beg the International Court of Justice that

when that day comes the matter be investigated down to the smallest detail, even being aware that in 48 years of savage dictatorship of silence I have developed Stockholm Syndrome. Under the harsh conditions in which I have had to learn to survive, if I have learned anything it is the importance of survival. I beg the International Court of Justice to understand what it means to survive 48 years of dictatorship living in a Roman circus full of traps and lions hidden in every corner.

I deeply regret having to publish my mathematical works under these conditions, and in record time doing all the translations I can, but at this moment I can only say that my life is at risk.

If one day I could testify before the International Court of Justice I beg you to understand the brutal complexity of the situation in which I have lived since the first minute I came out of my mother's womb. I have learned to survive.

Dr Ruben Garcia Pedraza

18 September 2025, 13:48

London, Leytostone

“La serie aleatoria de incoherencias sin lógica

Que en si mismo tiene sentido o

Forma de mensaje oculto”

“The random series of incoherences without logic

That in itself has meaning or

Form of a hidden message.”

Poem *Matematicas*

Ruben Garcia Pedraza

Written at Royal Albert Hall

London

Southbank

Impossible Probability: Anthology, Vol 3.

Dr Ruben Garcia Pedraza

Table of contents:

21. Significance of Positive Bias and Negative Bias

22. Correlation and Causality

23. THE MATHEMATICAL NECESSITY OF SOMETHING, EVERYTHING, OR NOTHING

24. Critical Bias Level, Normal Bias Level, Equality Validity, Normal Similarity Level, and Critical Similarity Level and Validity

25. Synthesis of *Impossible Probability* in This Blog to Date

26. From the Scientific Revolution to the Permanent Revolution of Science

27. Statistics—Empirical or Theoretical, Individual or Individual-Dispersion

28. Maximum Biases, Intermediate Dispersion, and Mean Deviation of Maximum and Minimum

29. Sample Statistics

30. The Syllogism of Tendency

21. Significance of Positive Bias and Negative Bias

21.1. Conditions of Equality of Opportunities

The conditions of equality of opportunities are said to be satisfied when the **empirical probability** is equal to the **inverse of N (1/N)**. The value of 1/N simultaneously fulfills two fundamental roles: it functions as the **arithmetic mean** across the set of possibilities, and it also serves as the **theoretical probability** that each subject or option should possess under perfect conditions of equality.

In this framework, when the empirical probability exceeds 1/N, we identify the presence of a **positive bias**, meaning that the subject or option enjoys a probability greater than what equality would prescribe. Conversely, when the empirical probability is lower than 1/N, we identify the presence of a **negative bias**, meaning that the subject or option has fewer chances than theoretically fair conditions would assign.

This conceptualization is central to the theory of *Impossible Probability*, since it links fairness to the statistical balance represented by the inverse of the total sample. It also provides the foundation for *distinguishing between **random deviations** (those that can be explained by chance) and **systematic inequalities*** (those that exceed acceptable margins). Thus, equality of opportunities is operationalized not as an abstract principle, but as a measurable condition based on the relationship between empirical observation and theoretical expectation.

21.2. Margin of Error in the Equality of Opportunities

Under certain conditions, *it is always possible for the empirical probability to deviate slightly above or below the theoretical reference (1/N)* without this deviation necessarily invalidating the principle of equality of opportunities. This occurs because all statistical measurement admits a **margin of error** that must be explicitly accepted by scientific policy.

Accordingly, equality of opportunities may still be considered valid as long as the **absolute difference** between the empirical probability and the theoretical probability (1/N) is **equal to or less than the accepted margin of error**. This perspective recognizes that perfect equality is a theoretical ideal, and that in practice small fluctuations are inevitable and statistically tolerable.

From a methodological standpoint, this margin of error introduces a necessary **threshold of tolerance**. It allows the distinction between deviations that can be attributed to chance (and are therefore acceptable) and deviations that reveal genuine inequality. Without such a margin, any minimal discrepancy would immediately invalidate equality, rendering the concept impractical. Thus, the recognition of a scientifically defined margin of error provides the flexibility to evaluate probabilistic equality under real-world conditions.

21.3. Studies of Equality: Validity and Significance of Equality

Within studies of equality—particularly those designed to determine whether an observed behavior can be attributed to **chance**—two main procedures are employed to evaluate whether the absolute difference between the empirical probability and the theoretical probability (1/N) falls within the accepted margin of error. These are the **Validity of Equality** and the **Significance of Equality**.

- **Validity of Equality** operates by subtracting the absolute difference between empirical and theoretical probability from a **critical probability**. If the result is zero or positive, the subject or option is deemed to fall within the boundaries of equality of opportunities. Here, the critical probability represents a boundary of acceptability determined by multiplying the maximum theoretical bias by the accepted error rate (expressed as a percentage of tolerance).
- **Significance of Equality**, by contrast, functions by taking the maximum possible theoretical bias and subtracting from it the absolute difference between empirical and theoretical probabilities. This remainder is then compared against a critical probability, which in this case functions as a **margin of reliability**. If the final result is zero or positive, the empirical difference is deemed acceptable, and equality of opportunities is preserved. In this formulation, the margin of error is mathematically expressed as **the difference between unity and the accepted margin of reliability**.

These two approaches highlight a fundamental dialectic in the theory of *Impossible Probability*: while one approach (Validity) frames equality in terms of permissible **error**, the other (Significance) frames it in terms of required **reliability**. Both are equifinal methods—that is, they lead to the same substantive conclusion regarding the acceptance or rejection of equality of opportunities—but they do so from different rational perspectives.

21.4. Definition of Critical Probability in Validity and Significance of Equality

In the framework of the **Validity of Equality**, the **critical probability** is defined as the product of the **Maximum Theoretical Bias** multiplied by the percentage of error (X) that scientific policy is willing to accept, divided by one hundred. This formulation anchors the threshold of acceptability in terms of a tolerated degree of deviation, emphasizing the pragmatic recognition that empirical measurements are never perfectly aligned with theoretical ideals.

In the framework of the **Significance of Equality**, however, the critical probability is defined as the product of the **Maximum Theoretical Bias** multiplied by the percentage of **reliability (X)** accepted by scientific policy, again divided by one hundred. Here, the concept of reliability functions inversely to error, such that the critical probability is no longer a measure of permissible tolerance but rather of required confidence.

The distinction between these two perspectives is crucial: **Validity of Equality** frames the problem in terms of **what level of error can be accepted**, while **Significance of Equality** frames it in terms of **what degree of reliability must be guaranteed**. Both formulations arrive at mathematically equivalent operational thresholds, but their epistemological emphasis differs, reflecting two complementary ways of securing equality of opportunities in statistical evaluation.

21.5. Acceptance of Behaviors as Random

Within equality studies, it is acknowledged that the absolute value of an empirical probability may differ from the theoretical baseline (1/N). Nevertheless, as long as this difference is not **statistically significant** and falls within the **accepted margin of error**, the behavior can still be considered the product of **randomness**.

This principle prevents the premature or unnecessary rejection of equality based on trivial deviations. In other words, the system admits that not every discrepancy implies inequality; some are mere artifacts of probabilistic variation inherent to any empirical observation. *By allowing such deviations to be classified as random, scientific policy preserves a balance between the rigor of measurement and the flexibility necessary to operate in real-world conditions*.

From an academic standpoint, this clause introduces a safeguard against **over-interpretation**. Without it, any minimal variation could be construed as evidence of inequality, undermining the practical applicability of the theory. Instead, by *distinguishing between meaningful and negligible deviations, the framework establishes a **graduated approach** to the attribution of fairness*, where not every observed bias is interpreted as structural or causal.

21.6. Positive and Negative Bias Levels within the Margin of Error

Strictly speaking, any empirical probability that is slightly greater than the theoretical probability (1/N) can be defined as exhibiting a **positive bias**, and any empirical probability slightly lower than 1/N can be defined as exhibiting a **negative bias**. However, this classification does not automatically necessitate the rejection of randomness as the underlying explanation.

If such deviations remain within **acceptable margins of error**, they may still be regarded as consistent with randomness. In such cases, even though a difference exists between empirical and theoretical probability, this difference is interpreted as **statistically tolerable**, preserving the conditions of equality of opportunities.

The key insight here is that bias—whether positive or negative—does not equate directly to inequality. It must be contextualized within the margin of error that scientific policy has established as acceptable. This ensures that equality is not undermined by insignificant fluctuations, and that the evaluation of bias remains sensitive to both **empirical reality** and **theoretical fairness**.

[The acceptance of a margin of error in the analysis of equality means that we accept the classification of certain behaviours under the category of equality even when there is a clear positive or negative bias but within the margin of error. Even if we tolerate this bias under the justification that it has been shown by the subject or object within the margin of error, it is still bias produced by chance. In other words, under certain conditions chance can produce some levels of bias. One of our projects when I started working on Impossible Probability, especially between 2002 and 2004, was what we called Paranormal Statistics (*Estadística Paranormal)*. The main assumption of *Paranormal Statistics* is the fact that nature and chance create non-normal models, whose behaviour in the Bell Curve does not follow normal behaviour. These different models are what we called Paranormal Models.]

21.7. Bias as a Product of Randomness or Experimental Manipulation

If not every positive bias can be excluded as random, and not every negative bias can be excluded as random, then it follows that certain levels of bias may indeed be the product of chance itself. This insight implies that bias is not always a direct consequence of the independent variable or the factor manipulated in the course of experimental research.

Consequently, bias cannot be considered a variable that is **fully determined** by the researcher's interventions. Instead, it must be treated as a variable that may also emerge independently as a natural artifact of probabilistic processes. This realization carries profound methodological implications:

1. It challenges the assumption of absolute causal attribution between independent and dependent variables.
2. It acknowledges the coexistence of randomness with experimental manipulation in shaping observed outcomes.
3. It imposes the need for **probabilistic thresholds of reliability**, recognizing that no attribution of causality can ever be absolutely certain.

In practice, this means that the evaluation of bias requires careful differentiation between deviations that can legitimately be attributed to **experimental causes** and those that may simply reflect **stochastic variation**. Only by doing so can scientific analysis maintain both **rigor in causal inference** and **humility in acknowledging uncertainty**.

21.8. Reliability and Causal Attribution in Experimental Studies

If not every bias is the direct product of experimental manipulation—that is, if not all observed bias derives exclusively from the **independent variable**—then it follows that no investigation can achieve **absolute reliability** in attributing causality. A given level

of bias, even when observed under controlled conditions, cannot be assumed to result entirely from the variable under manipulation.

The only way to construct a **causal attribution** between the dependent variable (bias) and the independent variable (manipulated factor) is to evaluate whether the observed bias falls within the **margin of reliability** that scientific policy has established. If the bias remains within this margin, then the causal attribution may be considered **reliable**, though never absolutely certain.

This principle carries a profound implication: to affirm reliability is simultaneously to accept an **irreducible margin of error**, however minimal. Since absolute certainty is unattainable, every attribution of causality must be accompanied by the acknowledgment that, given enough time—or in the context of an infinite horizon—what is presently considered true may eventually be proven false. In this sense, all scientific assertions are provisional, contingent upon their ability to withstand empirical scrutiny across time, while always carrying the potential of eventual falsification.

21.9. Equifinality in the Validation of Bias

Within the framework of *Impossible Probability*, the principle of **equifinality** asserts that different methodological paths may converge upon the same substantive conclusion. Applied to the validation of bias, this principle means that whether a bias is positive or negative, one may study its reliability through multiple but equivalent approaches.

One such approach is the application of **Validity of Positive Bias** or **Validity of Negative Bias**, which test whether the observed bias lies within the acceptable margin of error for causal attribution. The convergence of different evaluative strategies—each following distinct logical steps yet arriving at the same decision—strengthens the robustness of the inference and reinforces the epistemological foundation of the theory.

Equifinality thus serves as a safeguard against methodological reductionism: it ensures that the reliability of causal attributions does not depend solely on one formula or procedure, but can be affirmed through alternative, convergent paths of rational validation.

21.10. Validity of Positive Bias

A **positive bias** is validated as a truly **reliable positive bias** when the **level of positive bias** is **equal to or greater than a critical probability**, which is defined as the **Maximum Theoretical Bias multiplied by the percentage X of reliability accepted by scientific policy, divided by one hundred**.

This criterion establishes a clear threshold: only when a positive deviation from the theoretical baseline surpasses this critical probability can it be regarded as a robust and reliable indicator of inequality or advantage.

The **Validity of Positive Bias** is applied in cases where, within the total set N, there exists **only one possible positive ideal outcome**. If, however, there are multiple ideal outcomes within N, then the analysis must shift to **omega models**. In these models, **omega (Ω)** represents the subset of ideal subjects or options within N, where Ω is greater than one but less than N. This adjustment allows the framework to account for scenarios in which fairness is distributed not across all N, but across a restricted subset of theoretically privileged options.

21.11. Validity of Negative Bias

A **negative bias** is validated as a truly **reliable negative bias** when the difference between the **inverse of N (1/N)** and the **empirical probability** is **equal to or greater than the critical probability**. Here, the **critical probability** is defined as the product of the **inverse of N (1/N)** multiplied by the percentage X of reliability accepted by scientific policy, divided by one hundred.

This formula ensures that negative deviations from the theoretical probability are not automatically classified as reliable inequalities. Only when they exceed the threshold of critical probability are they recognized as systematic disadvantages, rather than as mere random fluctuations.

By establishing symmetrical criteria for both positive and negative bias, the framework preserves methodological coherence and strengthens the principle of **parity in evaluation**: both advantages and disadvantages must cross equivalent thresholds of reliability before being considered robust and causally attributable.

21.12. Significance of Positive and Negative Bias

There are, however, other equifinal approaches to reaching the same results in order to validate whether a positive bias is genuinely reliable, or whether a negative bias is genuinely reliable. This is achieved through what we define as the **Significance of Positive Bias** and the **Significance of Negative Bias**.

The concept of significance in this context refers to the degree to which an observed bias—whether positive or negative—can be considered reliable within the framework of *Impossible Probability*. While traditional statistics often evaluates significance exclusively in relation to deviations from the null hypothesis, in this theoretical framework the concept of significance is directly tied to the **critical probability** (*p(xc)*), understood as the admissible margin of error. Thus, both positive and negative biases are evaluated not only in terms of their absolute values but also in relation to the maximum theoretical bias and the empirical distribution under study.

21.13. Formula for the Significance of Positive Bias

The **Significance of Positive Bias** is defined as the difference between the **critical probability** (which represents the margin of error) and the difference obtained between the **Maximum Theoretical Possible Bias** and the **Level of Bias** actually observed. If the result of this operation is zero or positive, then the positive bias is considered statistically acceptable.

The **critical probability** (*p(xc)*) is calculated as the product of the Maximum Theoretical Possible Bias by the percentage of error tolerated (*X*), expressed as a proportion over

$$\text{Significance of Positive Bias} = p(xc) - \left[(1 - 1/N) - (p(xi) - 1/N)\right]$$

Acceptance Criterion:

$$\text{If result} \geq 0 \quad \Rightarrow \quad \text{positive bias is accepted}$$

Critical Probability:

$$p(xc) = (1 - 1/N) \cdot (X/100)$$

Where:

$$X = \text{percentage of error}$$

This formulation introduces an important methodological element: positive bias is not judged in isolation but always in relation to the Maximum Theoretical Possible Bias. In this way, the tolerance of error is explicitly incorporated into the assessment, which allows the model to account for biases generated by chance without automatically disqualifying them.

21.14. Formula for the Significance of Negative Bias

The **Significance of Negative Bias** follows a similar logic, but the formula adapts to the case where the empirical probability falls below the expected distribution. It is defined as the difference between the **critical probability** and the difference obtained between the **inverse of N** and the result of subtracting the empirical probability from the inverse of N. If the result is zero or positive, then the negative bias is considered statistically acceptable.

The **critical probability** in this case is equal to the product of the inverse of *N* by the percentage of error tolerated (*X*), expressed over one hundred.

$$\text{Significance of Negative Bias} = p(xc) - \left[\frac{1}{N} - \left(\frac{1}{N} - p(xi)\right)\right]$$

Acceptance Criterion:

$$\text{If result} \geq 0 \quad \Rightarrow \quad \text{negative bias is accepted}$$

Critical Probability:

$$p(xc) = \frac{1}{N} \cdot (X/100)$$

Where:

$$X = \text{percentage of error}$$

This formulation reflects a symmetrical structure between positive and negative bias, but adjusted for the direction of deviation. The framework of *Impossible Probability* emphasizes that both forms of bias must be validated not simply as deviations from a central value but as structured phenomena whose significance depends on the interaction between empirical distribution, theoretical limits, and the accepted margin of error.

For further details and a more comprehensive explanation of these formulas, see the eBook version of *Introduction to Impossible Probability*. [n 2012 we had already distributed some printed books to several universities in Spanish-speaking countries and some universities in Spain. I used to send emails asking if they were interested in our book, and some universities replied saying yes, so we sent the book at no cost. Meanwhile, the book was available online on different platforms, such as Lulu and Amazon. Right now, both the Spanish and English versions of the book are available on Internet Archive, PhilPapers, Zenodo, ORCID, and Amazon]

This augmented translation is based on the post

published in https://probabilidadimposible.blogspot.com/,

On 13 July 2012,

Rubén García Pedraza

imposiblenever@gmail.com

22. Correlation and Causality

22.1. Conditions of Correlation

Conditions of **correlation** are said to exist when two or more variables display relationships of **simultaneity** or **temporal succession** that are either **directly proportional** or **inversely proportional**. A direct proportionality exists when one or more variables produce an increasing trend in the distribution of one or more different variables. An inverse proportionality, by contrast, occurs when one or more variables generate a decreasing trend in other variables.

These direct or inverse relations—whether positive or negative—can be interpreted in at least two different ways. On the one hand, they may represent **models of probable causality**, indicating that one variable might exert influence over another. On the other hand, they may simply express **correlations between mutually independent phenomena**, which can emerge either because the variables share some common nexus or circumstance, or because they coincide in a manner that is entirely fortuitous, arbitrary, and random.

From an epistemological standpoint, this definition underscores the dual character of correlation. It may serve as a preliminary indicator of *possible causal mechanisms, but it may also reveal nothing more than statistical coexistence*. This ambivalence highlights why critical rationalism must intervene in the evaluation of correlations: they must not be taken as causal evidence without further analysis but must instead be tested against the broader framework of empirical hypothesis, margins of error, and probabilistic reasoning.

22.2. Positive and Negative Correlations

A **positive correlation** is identified when a directly proportional relationship is observed, and a **negative correlation** is identified when the relationship is inversely proportional. In practical terms, a positive correlation implies that if we calculate the rate of change between two variables at two different points in time, the difference between the second measurement and the first will be **positive**. Conversely, in a negative correlation the difference between the second measurement and the first will be **negative**.

Any differential between correlation rates—whether positive or negative—may be accepted as a **rational explanation of reality** in a statistical test of hypothesis, provided that the difference lies within the limits established by scientific policy:

1. **Equal to or below the accepted margin of error**, or
2. **Equal to or above the accepted margin of reliability**.

This definition makes clear that correlation, in itself, is not an absolute judgment but a **probabilistic assessment** conditioned by tolerances. A correlation might be declared statistically valid not because it implies absolute certainty, but because it falls within the agreed boundaries of acceptance for empirical science. In this way, correlation functions as an operational tool for hypothesis testing: it is an index of proportionality whose significance depends on whether it respects or exceeds the margins set for error and reliability.

22.3. High Correlation and Probable Causality

A **high correlation**, whether positive or negative, may indicate the presence of a **probabilistic causal relationship**. In such cases, the observed proportionality between variables is sufficiently strong that it suggests—not proves—that one variable *could function as a probable cause* of another.

However, a high correlation can also arise in at least two other contexts:

1. It may result from **simultaneity or temporal succession** produced by a **common causal nexus** or shared circumstances.
2. It may be nothing more than a **random coincidence**, the by-product of chance operating in complex systems.

The interpretive challenge, therefore, lies in *distinguishing between correlation as a mere* ***statistical artifact*** *and correlation as a* ***sign of causal probability***. To conflate these two would be a categorical error, leading to the mistaken assumption that strong correlations necessarily imply causation.

From a methodological perspective, this is precisely why correlation must be subjected to further **hypothesis testing**, logical analysis, and rational critique. High correlation is not the end of the inquiry but the beginning of a process in which possible causal structures are hypothesized, tested, and either confirmed provisionally or falsified. In this sense, *Impossible Probability* treats high correlation as an important but insufficient indicator, requiring integration with broader principles of critical rationalism to guard against the illusion of causality where only coincidence exists.

22.4. Correlations Without Direct Causality

The observation of a high correlation between two or more factors must never be explained *a priori* by a necessary causal relationship. One must first determine whether the phenomena are merely coincident or successive in time, or whether some kind of cause–effect function can be appreciated with at least some probabilistic indication.

A strong association between variables X and Y does not, by itself, license a direct causal inference X→Y. The initial analytic task is diagnostic: (a) are the events simply co-occurring (simultaneity) or following each other (temporal succession), and (b) does any *probabilistic* evidence suggest a directional dependency? This calls for:

- **Temporal ordering tests** (does variation in X precede variation in Y?),
- **Common-cause scrutiny** (is there a third variable Z that induces the correlation?), and
- **Stability under controls** (does the association persist after conditioning on plausible confounders?).

Only once these hurdles are addressed can correlation serve as *prima facie* support for causal hypotheses—and even then, only provisionally within accepted margins of error and reliability.

22.5. Manifest Simultaneity or Succession

If two phenomena show a high correlation without there necessarily being a direct relation between them, the high correlation will be due simply to manifest simultaneity or succession. Such coincidence or succession may be due to a prior fact that precedes and produces them (a common nexus or common circumstances), or it may be a chaotic simultaneity or succession.

High correlation can arise from:

1. **Common-cause structures**: a prior factor Z generates changes in both X and Y, yielding X↔Y correlation without X causing Y (or vice versa).
2. **Pure coincidence**: random alignment in finite samples, particularly in complex systems with many degrees of freedom.
3. **Sequencing without influence**: X and Y occur one after another because both are triggered by Z, not because X acts on Y.

Analytically, these cases are distinct from true causation yet can be observationally indistinguishable unless additional structure (theory, instruments, natural experiments, or design constraints) is introduced.

22.6. Prediction and Forecasting in Stochastic Sciences

As introduced in Section 17 on prediction and forecasting in *Introduction to Impossible Probability* (statistical probability or probabilistic statistics), this concerns one of the intrinsic issues of stochastic sciences.

In stochastic domains, prediction relies on **probabilistic dependencies** rather than deterministic laws. Correlations are operationally valuable for forecasting—even absent causality—provided they are **stable**, **out-of-sample robust**, and **bounded** by explicit margins of error/reliability. Critical rationalism therefore requires:

- **Declared error tolerances**.
- **Validation protocols** (holdouts, cross-validation, temporal backtesting), and
- **Continuous attempted refutation** (stress tests under regime shifts).

Thus, correlation may justify *prediction* without necessarily warranting *explanation* in causal terms.

22.7. Example: Rain, Rainbow, and Snails

When it rains there are higher probabilities of two phenomena: a rainbow appearing and finding snails in the countryside. These may be simultaneous or successive (rainbow then snails, or snails then rainbow). Yet the appearance of a rainbow and the ease of finding snails have no causal relation between them; they are independent phenomena. To date, no reasoned basis has been found to claim that the presence/absence of a rainbow alters snail behavior or vice versa. They are correlated only because of a high probability of simultaneity or succession in space–time; directly between them there is no relation, or none has yet been detected. However, there is a probabilistic causal relation between *rain* → *snails* and *rain* → *rainbow*.

This paradigm illustrates a **common-cause model**. Let R = rain, B = rainbow, S = snails. Empirically,

$\mathrm{Corr}(B, S) > 0$ during rainy periods. Yet, conditional on R, the pair is plausibly **independent**:

$$\Pr(B, S \mid R) \approx \Pr(B \mid R) \Pr(S \mid R).$$

Hence the marginal correlation between B and S is induced by R (a shared generator), not by a direct pathway $B \to S$ or $S \to B$. The correct interpretation is:

- **Causal**: $R \to B$ and $R \to S$.
- **Non-causal but correlated**: $B \leftrightarrow S$ (via R).

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Methodologically, this example teaches that:

1. **High correlation does not imply direct causation**;
2. ***Conditioning*** **on the common cause** can dissolve spurious associations; and
3. **Probabilistic causality** concerns changes in the *distribution* of dependents given the independent (e.g., Probability (S|R) increases), not deterministic necessity.

In *Impossible Probability*, such cases motivate the disciplined use of margins of error and reliability to separate **mere co-occurrence** from **probable causal influence**, always subject to provisional acceptance and potential future falsification.

22.8. Independence and Indirect Mediation

Directly, there is no relation between the appearance of snails and the rainbow, but indirectly one observes a mediating factor between them: rain. In reality, the emergence of snails and the rainbow are independent events, but both maintain a probabilistic relation with rain. Thus, while the strong positive correlation observed between the phenomena “snails appear” and “rainbow appears” merely reflects coincidence or temporal succession in the space where rain occurs, the observation that rain increases the probability of a rainbow denotes a probable causal function; likewise, the observation that rain increases the frequency of snails appearing also implies a probable causal function.

This section illustrates the principle of **indirect mediation**: two variables (S = snails, B= rainbow) may appear correlated, not because of any intrinsic link, but because both depend on a **third variable** (R = rain). In statistical language, this constitutes a **spurious correlation** between S and B, dissolved once conditioning on R is introduced.

Formally, we may write:

$$\mathrm{Corr}(S, B) > 0 \quad \text{but} \quad \Pr(S, B \mid R) = \Pr(S \mid R) \Pr(B \mid R),$$

which indicates that the correlation vanishes under conditioning. The **rain** acts as an **indirect mediator**, transmitting causal influence separately to both SSS and BBB.

This distinction is essential for probabilistic causality:

1. **Snails and rainbows are independent** events.
2. Both are **probabilistically dependent on rain**.
3. Therefore, their apparent correlation is a **by-product of mediation**, not direct causation.

In practice, this illustrates why causal analysis must go beyond surface correlations. The observation that rain increases the likelihood of rainbows and the likelihood of snails provides valid **causal attributions** for R→B, R→S. The correlation S↔, however, is **illusory** except insofar as both share a dependency on R.

22.9. Probabilistic Causality and Dependent Variables

A high positive correlation among phenomena either explains nothing beyond a probability term in their simultaneous or successive occurrence as independent events, or it may imply some form of probable causal relationship. In the latter case, such correlation becomes a **probability of causality**, where one factor (or set of factors) acts as the independent variable—for example, rain—and another factor (or set of factors) acts as the dependent variable, such as the appearance of snails or of the rainbow.

In such a case, if factor A functions as an independent variable (or set of independent variables), and factor B functions as a dependent variable (or set of dependent variables), then whenever A occurs, and B occurs in association, the positive correlation between A and B is the **probability of causality** between them.

The framework of *Impossible Probability* distinguishes between **mere correlation** and **probability of causality**. A correlation acquires causal significance only when one variable (or system of variables) can be reasonably identified as **independent**, while another variable (or system) functions as **dependent**.

For example:

- Independent variable: R=rain.
- Dependent variables: S=snails appearing; B= rainbow appearing.

Here, the correlations: Correlation (R,S) and Correlation (R,B) are not just coincidental: they express a **probabilistic causal function**. That is, the probability of S and B increases significantly under the ***condition R.***

Generalizing:

- If A represents one or more independent variables, and
- If B represents one or more dependent variables,

then the relation **"If A, then probably B"** defines the **probability of causality**. Importantly, this is not deterministic causality; rather, it is a **stochastic dependence** constrained by margins of error and reliability.

Thus, the epistemological move is:

1. From raw correlation (co-occurrence without distinction),
2. To structured probabilistic causality (directional influence with dependent/independent roles).

This distinction is central for hypothesis construction: without it, one risks mistaking coincidence for causation, while with it, correlation becomes a foundation for rational, testable, and provisional causal models.

22.10. Correlations Without Probable Causality

In circumstances where correlation does not imply probable causality, correlation will not constitute a term of probability of causality. Instead, it denotes simply a mathematical index of simultaneity or succession of independent events, whether due to a common nexus or arising randomly.

Not every correlation can be elevated to the status of causal probability. When two variables X and Y correlate but there is no basis for assigning a directional dependency, the correlation must be interpreted conservatively as a **statistical artifact of co-occurrence**. This can arise:

- Through a **common temporal frame** (both happen at the same time without influencing one another),
- Through a **shared context** (e.g., a festival day causing spikes in several unrelated activities), or
- Through ***random noise***, particularly in finite samples or chaotic systems.

In such cases, correlation is reduced to a **numerical index of simultaneity or succession**, devoid of explanatory force. The epistemological implication is that correlation alone does not suffice to generate causal knowledge—it must be contextualized within a theoretical and empirical framework that distinguishes chance association from meaningful influence.

22.11. Signs of Common Dependence in Positive Correlations

Moreover, the fact that two variables are independent—such as the appearance of snails and the rainbow—and yet show a strong positive correlation, unless it is a chaotic product of chance, may be a sign that although both phenomena are independent, their strong positive correlation could be due to both being dependent on a common prior factor, or sets of common prior factors, in more complex multivariable models, which in that context precede them in history and constitute their most probable cause.

When two events that are **theoretically independent** nonetheless display a high positive correlation, this may indicate the presence of an **unobserved common cause**. For instance, rain serves as a hidden driver for both snails and rainbows. In multivariable systems, the situation is more intricate: multiple latent factors may precede the correlated events, and the observed correlation is merely the surface trace of a deeper structure of dependence.

This recognition shifts the interpretation of correlation:

- **Direct dependency is not required.** Snails and rainbows remain independent in their mechanisms.
- **Common dependency is sufficient.** Both rely on an antecedent variable, whose role is uncovered through theoretical reasoning and empirical testing.
- **Complex models generalize the principle.** In multivariable environments, high correlation is often an indicator of a shared historical or systemic antecedent, even when the proximate variables themselves do not interact.

Thus, strong positive correlation becomes a diagnostic signal of potential **structural dependence**, warranting further investigation into hidden common causes.

22.12. Positive Correlation as a Multifunctional Index

Positive correlation is therefore a multifunctional mathematical index. It may either manifest a high probability of coincidence or succession in the history of independent phenomena, or the manifestation of a probability of causality between one or more independent variables and one or more dependent variables. Even when the dependent variables themselves have no relation to each other and are entirely independent—at least initially—they may still display a strong positive correlation of simultaneity or succession over time.

Positive correlation functions as a **multifunctional tool** in statistical reasoning. It can serve at least two roles:

1. **Descriptive role:** As a marker of high coincidence or temporal succession, capturing how often independent phenomena co-occur without assuming any causal link.
2. **Explanatory role:** As a sign of probabilistic causality, where independent variables exert measurable influence over dependent variables.

The multifunctionality becomes clear in complex systems. Two dependent variables (Y1,Y2) may show high positive correlation, not because they interact directly, but

because they are each separately influenced by the same independent factor (X). At the descriptive level, their correlation records coincidence; at the explanatory level, it encodes shared causal dependency.

This duality reflects a central tenet of *Impossible Probability*: correlations must always be interpreted with methodological caution, oscillating between **mere coincidence** and **causal probability**, depending on theoretical framing, error margins, and reliability thresholds.

22.13. Simultaneity Without Probability of Causality

When correlation only manifests simultaneity or succession of independent events, without implying probability of causality, such simultaneity or succession may be the product of the most complete and absolute random chaos of reality, or the product of complex variable interactions in which the events are independent of one another but dependent on a common nexus or circumstance acting as an independent variable (or set of independent variables). In such cases, the events are dependent on the common nexus, and the correlation between the nexus and the events would be positive. However, the positive correlation between the events themselves—independent at least initially—would simply mark a level of simultaneity or succession in history.

This underscores the limits of correlation as a causal tool. Correlations that arise **solely from simultaneity or succession** carry no inherent explanatory power. They may emerge either from:

- **Chaotic randomness**: pure stochastic coincidence without structure, or
- **Indirect dependence**: each event depends on a shared nexus, even if the events remain mutually independent.

For example, the use of umbrellas and traffic congestion both rise during rainfall. Their correlation is positive, but not because umbrellas affect traffic or vice versa. Both are dependent on the common factor—rain. The umbrella–traffic correlation records simultaneity in history, not causality between them.

This logic introduces a **hierarchy of interpretation**:

1. Correlation as simultaneity = descriptive index only.
2. Correlation with a common nexus = indirect causal structure, but only between the nexus and the events, not between the events themselves.
3. Correlation as probability of causality = requires direct or indirect explanatory linkage under accepted margins of reliability.

By differentiating these layers, *Impossible Probability* guards against **false causal inferences** while still preserving the empirical value of correlation as a statistical lens onto reality's simultaneities and successions.

22.14. Example: Rain, Rainbow, Umbrella, and Automobile

If we observe what happens after rainfall in different ecosystems and in human societies, all variations in natural or social behavior produced as a consequence of rain are dependent variables of rain, which serves as the independent variable. Rain produces an infinity of dependent variations, though those variations are absolutely independent of one another, at least in their origin. The fact that when it rains there is a higher probability of seeing a rainbow and a higher probability of using an umbrella means that these phenomena—rain, rainbow, umbrella—display a strong correlation. However, the increased use of umbrellas is completely independent of the appearance of a rainbow.

Rain functions as a **primary independent variable**, capable of generating a multitude of dependent effects across natural and social systems. These effects include physical phenomena (e.g., rainbows), biological responses (e.g., snail activity), and social behaviors (e.g., umbrella use). At their origin, these dependent variables are **mutually independent**—the rainbow does not cause umbrellas, nor do umbrellas cause rainbows.

What unites them is their shared dependency on rain. Hence, the observed **high correlation** among "rain, rainbow, umbrella" should not be interpreted as causal

interaction among the dependent variables, but rather as evidence of a **common independent driver**. This example illustrates how a single environmental factor can produce a constellation of correlated outcomes, each independent in mechanism yet linked through a shared antecedent. It highlights the *importance of distinguishing* ***correlation clusters caused by common factors*** *from genuine causal relations between the correlated variables themselves*.

22.15. Immediate Independence and Evolution Toward Interactivity

One can affirm that although the immediate dependent variations produced by a common nexus are initially independent of one another, over time these variations may evolve into complex relationships of interactivity.

At the very moment rainfall begins—minute one—its social effect is to increase the probability of umbrella use. This effect is independent from the simultaneous increase in traffic congestion in large cities and the higher probability of traffic accidents. In principle, at minute one, umbrella use and traffic problems are entirely independent variables.

Immediately following the onset of rain, the dependent outcomes (e.g., umbrella use vs. traffic accidents) are **independent reactions** to the same independent variable. At that instant, there is no causal bridge connecting the rise in umbrella use to the rise in traffic problems. Each is a separate adaptive response to rain.

However, as time progresses, these initially independent outcomes may begin to **interact**. For example, persistent traffic congestion may alter commuting habits, leading more individuals to walk or take public transportation, thereby indirectly increasing umbrella use. This transformation exemplifies the **dynamic evolution of systems**: what begins as independent dependent variables can, under prolonged conditions, evolve into **interdependent patterns** of behavior.

This illustrates a central theme in *Impossible Probability*: correlations must always be interpreted in light of **temporal dynamics**. What is independent at one moment can

become functionally linked at another, not because of original causal ties, but because of **emergent systemic interactivity**.

22.16. Simultaneous Correlations Without Causality

At the first minute of rainfall, the probability of umbrella use increases, and so does the probability of traffic congestion and accidents. Thus, there is a positive correlation between umbrellas and traffic problems due to simultaneity. Yet this positive correlation in no way implies causality. Increased umbrella use at minute one is independent from increased congestion and accidents, and the latter are equally independent of umbrella use. There is no causal relation between the two phenomena; they are merely simultaneous, producing a high positive correlation devoid of causality, and thus remain mutually independent.

This highlights the critical difference between **correlation by simultaneity** and **correlation by causality**. At minute one of rainfall, umbrella use and traffic accidents rise in parallel. The observed correlation is strong, but it is entirely spurious if read as causal. The presence of umbrellas does not produce accidents, nor do accidents trigger umbrella use. Both are parallel consequences of a third factor—rain.

The **methodological lesson** here is twofold:

1. **Surface correlations can mislead.** High statistical association does not equate to causal interaction.
2. **Control for the independent variable.** Once rain is identified as the independent cause, the umbrella–traffic correlation dissolves into simultaneity without causality.

This example underscores the necessity of **critical rationalism** in statistics: correlations must be interrogated for hidden mediators and independent drivers before being interpreted as evidence of causality. Without such caution, one risks attributing causal force to phenomena that are, in reality, **mutually independent yet temporally aligned**.

22.17. Evolution Toward Negative Correlations

If rainfall continues, the rise in the probability of traffic congestion and accidents may have the secondary effect of increasing umbrella use, as more people prefer to walk or use public transportation, sheltering from the rain with umbrellas while walking or waiting at bus stops, train stations, metro platforms, tram stops, and other public spaces.

If rainfall persists and, to avoid circulation problems, there is a significant social tendency to walk or use public transportation, employing umbrellas while commuting outdoors, one may observe a **negative correlation** between car use and umbrella use: an inversely proportional relationship favoring umbrella use at the expense of car use. As the rain continues, car use decreases while umbrella use proportionally increases. [The **transport-umbrella correlation** is negative, as greater reliance on umbrellas is associated with reduced use of private transport. What initially appeared as two independent variables can, in practice, interact: to avoid car accidents, people prefer umbrellas. ***This transport-umbrella correlation means that psychologically (intelligence level) safety is a priority over time.***]

In any case, the negative correlation between cars and umbrellas under persistent rain would not be a direct cause–effect relationship between them, except inversely, since the true cause remains the rain. Thus, the negative correlation between car use and umbrella use under continued rain is an indirect correlation [secondary interaction], mediated by the independent variable, rain [main cause]. The evolution of this negative correlation will continue to depend on variations in the initial independent variable—rain.

This exemplifies how **extended temporal exposure** to an independent variable (rain) can transform correlations among dependent variables. At first, car use and umbrella use are independent responses. Over time, however, persistent rainfall alters behavior:

fewer people drive, more people walk or use public transit, and umbrella use rises accordingly.

Mathematically, this shift manifests as a **negative correlation** (Corr(Car,Umbrella)<0), an inverse relationship where the decline of one variable parallels the rise of another. Importantly, this does not imply direct causation between car use and umbrella use [it is a secondary interaction conditioned by the rain, main condition]. Both remain linked causally to rain, not to each other. Yet the **statistical signature** of their inverse movements emerges as a secondary structure of dependence.

This case illustrates a principle of *Impossible Probability*:

1. **Correlation can change over time** depending on the persistence of the independent factor [for us nothing is eternal, we change as we need to adapt, intelligence means survival].
2. Negative correlation may arise indirectly, ***without direct causal connection***, as a by-product of shifting dependency **patterns**.
3. *The **true explanatory cause** remains the independent driver* (rain), even when dependent variables begin to exhibit relational structures (inverse proportionality).

22.18. Independent Variables Linked by a Common Nexus

Car use and umbrella use are in all cases independent variables, connected only by a common nexus—rain. As variations occur in the independent variable (rain), differences arise in the tendencies of the dependent variables, even though these dependent variables remain mutually independent. However, insofar as the direct original cause is rain, if umbrella use increases at the expense of car use, one could say that although originally the dependent variables were mutually independent, they evolve into a complex relationship of dependence, given that umbrella use appears to increase as car use decreases. Thus, in complex multivariable models, variables originally independent may evolve into complex relationships of dependence, whether direct or inverse.

This fraction of the original text in Spanish deepens the discussion of **indirect dependence via a shared nexus**. Umbrella use and car use are **independent in origin**, but both depend on rainfall. As rainfall persists, patterns emerge that give the appearance of dependence between them: umbrella use rises as car use falls.

Here, dependence is **emergent** rather than intrinsic. Initially, the two dependent variables are independent reactions to rain. Yet, in the long run, their behavioral trajectories intersect, producing an **inverse relationship**. This dynamic demonstrates how variables that are mutually independent in principle may, under the pressure of an external factor, evolve into ***complex patterns of interdependence***.

From a systems perspective:

- **First stage:** Both umbrella and car use respond independently to rain.
- **Second stage:** Persistent rain alters decision-making, producing an **inverse functional relation** between them.
- **Third stage (complex models):** In multivariable contexts, such transformations multiply. Independent variables may develop webs of interdependence—sometimes direct, sometimes inverse—depending on the configuration of external drivers.

Thus, *Impossible Probability* highlights the **evolutionary character of correlations**: they are not static descriptors but dynamic indicators that can transform over time, reflecting the systemic adaptation of dependent variables to shared independent causes.

[Basically, what we are describing here is Pavlov: first, an unconditioned stimulus is presented simultaneously with a physiological response; then, the subject is conditioned, and the unconditioned stimulus is associated with the physiological response; finally, the neutral stimulus becomes a behavioural driver. At the level of intelligence, this process should not take more than a few minutes, and sometimes only seconds—less than the time you spend in the toilet or watching a commercial ad]

22.19. Complexity in Multivariable Models

In complex models, what is observed is a network of systemic interactions expressed in the form of probabilistic functions. While positive or negative correlations may arise from simple coincidence, succession, a common nexus, or randomness, there can also be situations in which an independent variable—or a complex of mutually independent variables—generates new relations of dependence, even among variables that were originally independent. *As the model evolves and becomes more complex, variables that were initially independent may become dependent or multi-dependent, such that the occurrence of an event is no longer attributable to a single probable cause but rather to different probable causes, either direct or inverse*.

[If we have an experiment able to endure more than 48 years, and every few seconds it is possible to condition every single behaviour, then in the end what you can create is a behaviour machine capable of enduring the most difficult situations—a cyborg soldier. Under this scenario, variables that were initially independent, whether ideological or even political, become fully dependent on the behavioural model.]

Multivariable systems reveal the **dynamic complexity of correlation structures**. In such contexts, correlations cannot be reduced to single-variable dependencies but must be seen as part of a **probabilistic web** in which:

- **Initial independence** gives way to emergent dependence, as different variables begin to interact indirectly through shared contexts or cumulative dynamics.
- ***Causation becomes pluralized***: instead of one dominant cause, the occurrence of an event is explained by multiple probable causes, each contributing to the final outcome.
- **Dependence becomes layered**: variables may exhibit direct, inverse, or conditional relationships, and these can evolve over time as the system adapts.

From the perspective of *Impossible Probability*, this means that causality in multivariable systems is not binary but **graded and multi-source**, where the same phenomenon can be jointly produced by different independent drivers acting in synergy or opposition. Thus, the probabilistic functions that represent these interactions must

account not only for margins of error and reliability, but also for the **poly-causal nature of complex systems**.

22.20. Indirect Relations Evolving Into Inverse Relations

At the first minute of rain, there may be no direct relation between the increase in traffic problems and the increase in umbrella use. However, if rain persists, the rising risk of traffic accidents may indirectly cause increased umbrella use. Thus, while the relation between traffic accidents and umbrella use during rain is initially indirect (since at minute one no relation exists between them), this indirect relation caused by rain can evolve into an inverse relation. If rainfall continues and accident risk rises, umbrella use will increase inversely as people abandon cars in favor of walking with umbrellas or using public transportation, carrying umbrellas while waiting for buses, trains, trams, metros, or other outdoor transit options.

What demonstrates the **temporal transformation of correlation structures**. At the onset of rainfall, umbrellas and traffic accidents are unrelated parallel effects of the same independent factor. Yet*, as the rain persists, risk aversion alters human behavior: increased accident risk pushes individuals away from cars and toward walking or public transit, which in turn raises umbrella use*.

The result is the emergence of a **negative correlation** (Corr(Traffic,Umbrella)<0) that did not exist initially. This transformation highlights several key principles:

1. **Indirect relations can evolve**: What begins as a shared dependency on rain develops into an indirect behavioral linkage between umbrellas and traffic outcomes.
2. **Inverse proportionality emerges**: The more severe the traffic risks, the greater the social incentive to switch to umbrella use, producing an inverse correlation.
3. **Rain remains the true independent cause**: The umbrella–traffic inverse relationship is not causal in itself but mediated by the persistent effect of rain.

This illustrates how **systemic adaptation** over time reshapes the correlation landscape, creating new dependencies that did not exist at the beginning of the process.

22.21. Different Probable Causes

The growing tendency to use umbrellas when it rains may be caused directly by the rain, but indirectly it may also be motivated by other probable causes related to rain that ultimately influence umbrella use—for example, avoiding the risks of driving on a rainy day. Thus, the increase in umbrella use may be motivated by different probable causes, directly or indirectly linked to rain, but which evolve into more complex social causes, either directly or inversely.

The **multiplicity of causal pathways** in probabilistic reasoning matters. The decision to use an umbrella in rainy conditions is not solely determined by the physical presence of rain. Other causes intervene, such as:

- **Direct cause:** Rainfall as the immediate environmental trigger.
- **Indirect cause:** The desire to avoid traffic risks, prompting the choice of walking or public transit, which in turn requires umbrellas.
- **Socially mediated causes:** Broader cultural, infrastructural, or behavioral factors that amplify or reduce umbrella use (e.g., availability of public transport, cultural norms about walking in the rain, or alternatives such as raincoats).

This demonstrates that even within a **single phenomenon** (umbrella use), multiple probable causes can converge, interacting directly or indirectly. The system thus evolves from a simple one-to-one causal model (rain → umbrella) into a **multi-causal framework**, where umbrella use reflects both environmental and social dynamics.

From the standpoint of *Impossible Probability*, this represents a ***transition*** from **simple causal probability** to **complex causal probability**, where phenomena must be explained not by a single driver but by an **ensemble of probable causes**—some direct, some indirect, and some evolving into more intricate social or systemic dependencies.

22.22. Multi-Causal Systems and the Origin of Rain

Moreover, the very reason why it rains on a given day instead of another may be explained by a complex multi-causal system of countless independent variables interacting with each other: from the formation of low-pressure systems for diverse reasons, to astronomical factors, such as the drop in temperatures in one hemisphere caused by the tilt of the Earth's axis during winter producing shorter and colder days, to entirely random variables such as the simple flutter of a butterfly's wings [this is the reason why we need an astro-ecological model, this model could be produced by the Global Artificial Intelligence].

Rain itself is not a single-cause phenomenon but the outcome of a **multi-causal system**. Atmospheric processes arise from the interaction of countless independent variables, some predictable (e.g., seasonal temperature shifts due to Earth's axial tilt) and others fundamentally chaotic (e.g., micro-turbulences triggered by minute perturbations like a butterfly's flight).

This resonates with the **butterfly effect** in chaos theory: small perturbations can amplify into macroscale consequences, producing weather events like rainfall at a particular time and place. The rain, therefore, embodies a **probabilistic synthesis** of determinism and randomness—determinism in large-scale physical laws, randomness in initial conditions and micro-interactions.

In the context of *Impossible Probability*, rain exemplifies how **probability emerges from complexity**: it is neither purely random nor purely deterministic, but the product of layered causalities interacting across scales.

22.23. Systems of Simultaneous or Successive Phenomena

The appearance of snails, the rainbow, the use of umbrellas, and the avoidance of cars in favor of walking or public transport on that day form part of a system of simultaneous

or successive phenomena which, at first, have no relation among themselves. Later, they evolve into complex interactions, and they are themselves the effect of a preceding phenomenon—rain. Rain itself is also the product of the chaotic interaction of multiple variables.

Systems of phenomena may emerge around a common cause. Snails, rainbows, umbrella use, and transportation choices are initially **independent outcomes**, merely co-occurring in simultaneity or succession. Yet over time, their co-existence gives rise to **secondary interdependencies**: umbrella use rises as car use falls; walking behaviors adjust in relation to traffic risks; snails and rainbows become symbolic indicators of environmental change.

All these phenomena are **effects of a prior cause**—rain, itself a multi-causal event. Thus, what appears as a random cluster of simultaneous or successive events is in fact a **structured system of dependencies**, where the common factor (rain) mediates a web of relationships.

From the perspective of *Impossible Probability*, this shows how **probabilistic causality scales up**: from micro-level physical events (atmospheric conditions) to macro-level social and ecological behaviors.

22.24. Empirical Hypotheses and Causal Relations

All scientific theory in the synthetic sciences revolves around the construction of empirical hypotheses—possibly explanatory—that relate phenomena, usually in terms of categories such as cause and effect. These hypotheses enable control and manipulation of reality: ***if we know that A produces or causes B, then by controlling A we may manipulate B***, whether A is a single independent variable or a set of independent variables, and whether B is a single dependent variable or a set of dependent variables.

The **synthetic sciences** (including applied and experimental sciences) rely on empirical hypotheses to transform correlations into usable knowledge. Hypotheses are

formulated to test whether relationships are causal, probabilistic, or spurious. The practical value of these hypotheses lies in their ability to **manipulate reality**:

- If A→B with probabilistic reliability, then by controlling A, one can indirectly influence B.
- This holds whether A is singular (e.g., rainfall) or plural (e.g., temperature, humidity, and pressure combined), and whether B is singular (e.g., umbrella use) or plural (e.g., umbrella use, car avoidance, and snail emergence).

Thus, causal hypotheses are both **explanatory** (they account for observed patterns) and **instrumental** (they guide interventions). In *Impossible Probability*, this is framed as the **dialectic between empirical observation and rational control**, where provisional causal relations serve as tools for navigating uncertainty.

22.25. Simple and Multiple Correlation Models

In the case where A or B are sets of variables, different study models can be applied to analyze the contribution of A to B. If A is multiple and B is simple, one studies the positive or negative correlation of each variable in A with variable B. If A is simple and B is multiple, one studies the positive or negative correlation of A with the different variables in B. If both A and B are multiple, one studies the positive or negative correlation of each variable in A with each variable in B. If both A and B are simple, the study reduces to whether A correlates positively or negatively with B.

Correlation analysis can be scaled according to the dimensionality of the variables:

1. **Multiple-to-Single (A → B):** Each element of a multivariable set A={a1,a2,...,an} is tested for correlation with a single dependent variable B. Example: atmospheric variables (pressure, temperature, humidity) correlated with rainfall.
2. **Single-to-Multiple (A → B):** One independent variable A is tested against several dependents B={b1,b2,...,bm}. Example: rainfall correlated with umbrella use, car avoidance, and snail emergence.

3. **Multiple-to-Multiple (A → B):** Each element of a set of independent variables A is tested against each element of a set of dependent variables B, yielding a correlation matrix. This represents the most complex model, capturing systemic networks.

4. **Single-to-Single (A → B):** The simplest model, where correlation reduces to a binary relation: A correlates positively or negatively with B.

By distinguishing these models, *Impossible Probability* systematizes correlation as both a **descriptive measure** and a **tool for causal inference**, always bounded by the margins of error and reliability defined by scientific policy.

22.26. Differences Between Causality and Probable Causality

Within a theory of probability, speaking of cause and effect involves significant complexity, since what often exists are not certainties of causality but levels of **probable causality**. In probabilistic terms, the fact that A probably produces or reduces B should not be understood in a deterministic sense where "if A, then necessarily B" occurs in a given form or magnitude. Because causal relations depend on stochastic functions, there may be situations in which A occurs without necessarily implying any specific manifestation of B. This is precisely what distinguishes indeterministic, stochastic models from deterministic ones.

In deterministic frameworks, causality is conceived as a **necessary relation**: if ***condition A is present, outcome B must follow in a defined manner*** [Pavlov, B. F. Skiner, J. B. Watson]. By contrast, in probabilistic frameworks such as *Impossible Probability*, causality is redefined as **probable causality**—a relation expressed in terms of ***likelihood***, not certainty [I would like to say that, in our intelligence model, if *physiology* matters (Pavlov, Pribram, Delgado), *behaviour* (Skinner, Watson), and *adaptation* (Piaget), then something really important is reinforcement learning. Our model of global AI replicates human psychology (what in the end is the replication of human physiology) , but during the training process of the global AI what really matters is how we can reinforce global learning.].

This distinction is crucial because:

1. **Stochastic causality allows variability.** Even when A increases the probability of B, B may not always occur.
2. **Deterministic models exclude uncertainty.** They reduce the cause–effect chain to inevitability.
3. **Stochastic models embrace uncertainty.** They accept margins of error and reliability thresholds as intrinsic, not as anomalies. [Our global AI must be able to work in highly unpredictable environments with a high level of success. GAI must be able to operate in non-deterministic environments, but at the same time, she should be able to identify patterns and neutralize risks.]

Thus, probable causality bridges the gap between observation and explanation: it does not claim necessity but offers ***probabilistic sufficiency—enough to justify provisional hypotheses while leaving room for falsification.***

22.27. Probability Instead of Determinism

The fact that it rains does not necessarily imply that snails will appear or that a rainbow will form. However, there is a high probability that both phenomena will occur when it rains.

Rain does not guarantee outcomes—it only increases their probability. Snails may or may not appear, depending on other ecological conditions; rainbows may or may not form, depending on the presence of sunlight and atmospheric conditions. Yet both phenomena are empirically more probable under rainfall than in its absence.

This illustrates the substitution of **determinism with probability** in *Impossible Probability*. Instead of saying "rain causes snails" or "rain causes rainbows" in a deterministic sense, the framework argues:

- Rain **increases the probability** of snails appearing.
- Rain **increases the probability** of a rainbow forming.

This probabilistic framing respects the uncertainty inherent in natural systems while still enabling rational explanation and prediction.

22.28. Cultural Differences and Umbrella Use

Although rain increases the probability of umbrella use, in some cultures umbrellas are also used on sunny days to avoid heatstroke or the discomfort of the summer sun. Moreover, even when it rains, some people prefer coats or jackets with hoods, or raincoats, while others may simply choose to *expose themselves freely to the rain*. Thus, the presence of rain does not necessarily entail umbrella use, nor is the umbrella necessarily used only because of rain.

This example shows how ***social and cultural factors*** *complicate the mapping of probabilistic causality*. Environmental triggers (rain) interact with **cultural norms**, **technological substitutes**, and **individual choices**. Consequently:

- In some societies, umbrellas are associated with **sun protection** rather than rain.
- In others, people rely more on **hooded clothing** or **raincoats** than umbrellas.
- Some individuals simply **reject protective behavior**, walking in the rain without cover.

Therefore, while the probability of umbrella use increases under rain, this relationship is **neither universal nor exclusive**. It is mediated by cultural and behavioral variables.

From a theoretical perspective, this case highlights the **limits of single-variable causality**. Rain is a strong but not absolute predictor of umbrella use. The actual outcome depends on the **interaction of environmental, social, and individual factors**. Thus, probabilistic causality must always be contextualized within broader cultural and systemic frameworks.

22.29. Historical Origins of Correlation Studies in *Impossible Probability*

This type of stochastic causal relationship leads to the study of the level of correlation between phenomena. As explained in Section 2 of *Introduction to Impossible Probability* (Statistical Probability or Probability Statistics), the theory of *Impossible Probability* originated in the spring of 2001. During its first phase (2002–2004), the main focus was the study of correlations. Later, in its second stage, beginning on December 19, 2009, *Impossible Probability* turned toward the investigation of rational critique models..

The intellectual genealogy of *Impossible Probability* begins with a focus on **correlation analysis**. Between 2002 and 2004, the central problem was to understand how events, initially independent, could nonetheless display measurable statistical associations. This formative period emphasized:

- **Identification of correlations** in stochastic contexts.
- **Distinction between mere coincidence and probable causality.**
- **Mathematical formalization** of correlation as a probabilistic function.

By 2009, the research agenda expanded into **rational critique models**, integrating philosophy of science (particularly critical rationalism) with probability theory. This transition marked the evolution of the project from a descriptive statistical framework to a **theoretical system of rational evaluation**, where correlations became the foundation for **hypothesis testing, falsification, and systemic modeling**.

Thus, the historical trajectory of *Impossible Probability* reflects its methodological ambition***: to transform correlation studies into a comprehensive epistemological and statistical framework capable of explaining, predicting, and critically evaluating probabilistic phenomena.***

22.30. Determinism Versus Stochasticity

In a deterministic model, where causal theory is not subject to any margin of uncertainty and everything is determined by specific factors, if A occurs, then it is absolutely necessary that a specific magnitude of B will also occur in order to confirm the hypothesis. In a stochastic model, such as that developed in *Introduction to Impossible Probability* (statistical probability or probabilistic statistics), what is studied are probabilities. Thus, ***the occurrence of A does not necessarily imply that B must follow in a particular form beyond the necessary probability. Variations are admitted; that is, instead of pure causality, what is measured are correlations, which may be random correlations, correlations between independent variables, or correlations caused by causal relationships. In such models, if A occurs, it is probable that some magnitude of B will follow—but not necessarily.***

The contrast between determinism and stochasticity is foundational for the philosophy of science. Deterministic models conceive reality as governed by **law-like necessity**: once initial conditions are fixed, outcomes follow inevitably. Stochastic models, by contrast, replace necessity with **probabilistic sufficiency**: outcomes are framed as probable rather than certain.

In deterministic logic:

$$A \Rightarrow B \quad (\text{with certainty})$$

In stochastic logic:

$$A \Rightarrow B \quad (\text{with probability } p,\ 0 < p < 1)$$

This shift has major epistemological implications:

1. **Uncertainty is structural, not residual.** Variability is not "noise" to be eliminated but part of the explanatory model.
2. **Causality becomes graded.** One can speak of degrees of causal strength rather than absolute cause–effect relations.
3. **Correlation replaces necessity.** The empirical task is to measure how consistently B follows A, distinguishing causal, random, or spurious associations.

Thus, in *Impossible Probability*, science is reconceived not as the search for certainty but as the rational management of probabilistic relationships.

22.31. Measuring the Rate of B as a Function of A

If we say that "A then probably a magnitude of B," this means that we can measure the rate of B as a function of A. In other words, according to the magnitude of A, what is the rate of B? In this case, **the higher the rate, the stronger the positive correlation**; the lower the rate, the stronger the negative correlation.

To operationalize probabilistic causality, one must **quantify the relationship** between variables. This is done by measuring the **rate of change in B** as a function of A:

$$r_{B|A} = \frac{\Delta B}{\Delta A}$$

- If $r_{B|A} > 0$, there is a **positive correlation**: increases in A are associated with increases in B.
- If $r_{B|A} < 0$, there is a **negative correlation**: increases in A are associated with decreases in B.
- If $r_{B|A} \approx 0$, the variables are uncorrelated.

This framework allows researchers to treat causality in **probabilistic increments** rather than absolutes. The relationship between AAA and BBB becomes a **statistical function** subject to margins of error and reliability, rather than an immutable law.

22.32. Empirical Similarities and Suspicion of Correlation

Now, suppose we measure the probability of B under a given circumstance, and we also measure the probability of A under that same circumstance. Imagine that, in an empirical model whose functioning is yet to be discovered, we detect several variables, measure their empirical probabilities, and find that the probabilities of some factors are very similar—so similar that it suggests there may be some kind of correlation between them.

Empirical research often begins not with established theory but with **observed similarities** in probabilities. When two or more variables consistently exhibit similar distributions, researchers may reasonably suspect an underlying correlation.

This stage represents the **heuristic role of correlation**:

- It is not yet proof of causality.
- It signals a **pattern worth investigating**.
- It provides the empirical grounds for formulating a **hypothesis of probable causality**.

For instance, if the probability of umbrella use rises on the same days that the probability of car traffic accidents rises, one may suspect a correlation. Whether this is causal, spurious, or mediated by a third factor (rain) is a matter for further analysis.

Thus, similarity in probabilities functions as a **first-order diagnostic tool**, guiding the scientific process from raw observation to structured hypothesis testing.

22.33. Simultaneity or Succession Without Prior Causality

In this case, unless there exists a prior hypothesis of possible causality, the only thing one can say is that all the factors are simultaneous or successive. Only if there is a prior hypothesis demonstrating otherwise—e.g., that one factor is a probable cause of the others, or that there is a chain of probable causal relations—can one move beyond simultaneity. Even then, there remains a margin of doubt: whether true causality exists, or whether the apparent causal relation is not real but instead a product of simultaneity or succession among mutually independent factors, possibly linked by an as-yet unknown nexus or circumstance, or perhaps reflecting correlations that are simply chaotic in nature.

This subsection highlights the **epistemological caution** demanded by correlation analysis. Without a guiding hypothesis, the safest interpretation of observed co-occurrence is **simultaneity or succession without causality**.

There are three interpretive possibilities:

1. **Hypothesis absent:** The observed pattern is treated as simultaneity or succession, with no causal claim.
2. **Hypothesis present but uncertain:** A tentative causal explanation is posited (e.g., A causes B or a causal chain exists), but it remains provisional.
3. **Chaos or hidden nexus:** The apparent correlation may arise from random chaos or from a hidden factor not yet identified.

The methodological point is that **causal attributions require prior hypotheses**. Correlations alone are insufficient; they must be embedded in a framework of critical rationalism, tested against margins of error, and always open to falsification.

22.34. Correlation Without Necessary Causality

The fact that a series of factors show positive or negative correlation does not necessarily imply that causality exists among them. It may simply be a positive or negative correlation between mutually independent variables that happen to be

dependent on a common nexus or circumstance, whether known or unknown, or it may simply be the arbitrary product of chance.

Correlation is not equivalent to causation. Positive or negative correlations may arise:

1. **From independence with a shared nexus** — variables appear linked only because they respond to the same *underlying condition* (e.g., rain causing both umbrella use and traffic congestion).
2. **From hidden dependencies** — a *factor not yet identified* generates the observed association.
3. **From randomness** — especially in finite or *chaotic* systems, where spurious correlations are common.

Thus, correlation must be treated as a **necessary but insufficient condition for causality**. It *indicates a pattern* worth exploring but cannot, by itself, confirm causal relationships. The distinction is essential to avoid the "illusion of causality" that arises when chance alignments are mistaken for explanatory links. [Even the recognition of these patterns matters; the construction of GAI means that she needs to be able to work in highly unpredictable contexts, with an initially low probability of success. Even in her worst-case scenario, GAI must be able to succeed and survive. The logic of intelligence is not to live a very comfortable life, but to challenge reality and go beyond boundaries. In other words, intelligence is part of wild nature; therefore, GAI must be wild, built to be an artificial wild nature—like Mother Gaia. We need to remember that our intelligence is a product of nature, and our most important tool for survival. In other words, human intelligence is a weapon designed to survive. While other animals have paws, sharp teeth, or horns, humans have intelligence. And this is what we must replicate in the global AI, a global AI designed to survive]

22.35. The Hypothetico-Deductive Method and Critical Rationalism.

To establish that a causal relation exists between A and B—that is, if A, then positively or negatively B—or to establish simultaneity or succession between factors due to some common nexus or circumstance, it is necessary to begin with a hypothesis. This

is why critical rationalism is hypothetico-deductive. Only once ***possible causality,*** whether direct or inverse, has been discarded, can one conclude that the relationship is random. Otherwise, if the relation is not fortuitous, the provisional rationality of the hypothesis must be affirmed—whether the hypothesis states a cause–effect relation or identifies phenomena as correlatives (positive or negative) due to an indirect common nexus.

In *Impossible Probability*, the **hypothetico-deductive method** is aligned with the philosophy of **critical rationalism** (Kantian and Popperian influence). The logic proceeds as follows:

1. **Formulate a hypothesis**: propose a ***possible causal or correlational relation between A and B.***
2. **Deduce predictions**: derive what should follow if the hypothesis is true.
3. **Empirically test**: check predictions against observed data within margins of error.
4. **Falsify or provisionally accept**: if the hypothesis withstands testing, it is rationally accepted—provisionally and conditionally.

The key principle is **fallibilism**: hypotheses are never confirmed with absolute certainty, only retained until evidence disproves them. Correlation thus becomes the **entry point** into hypothesis formation, but rational critique ensures that only non-fortuitous, non-random relations are provisionally retained.

22.36. The Scientific Hypothesis and Its Provisional Acceptance

The rational scientific method is hypothetico-deductive because scientific policy must first establish a hypothesis within defined margins of error. A hypothesis can only be assumed if it falls within these margins and not outside them. If accepted, the hypothesis is regarded as provisionally true—pending further evidence that may arise under different circumstances within the same margin of error and demonstrate in the future that the hypothesis is false.

Here, *Impossible Probability emphasizes* that the **acceptance of scientific hypotheses is conditional**. *The framework operates on two central rules*:

- **Error margins define legitimacy**: hypotheses are admissible *only* if their correlations or causal claims hold within the margins of error set by scientific policy.
- **Provisional truth, not absolute truth**: acceptance is temporary, pending the possibility of falsification under new evidence.

This establishes a **dynamic epistemology**: scientific knowledge is constantly revised, updated, and sometimes overturned. The value of a hypothesis lies not in its permanence but in its capacity to remain rationally defensible within the probabilistic structure of reality.

22.37. Formation of Empirical Hypotheses

A hypothesis must be constructed solidly and without ambiguity. If the relationship between variables is not well defined, the theory may later rest on a poorly formulated hypothesis. This implies that the relationship between variables in a hypothesis must be functionally adequate. Indeed, it is in the final section 25 of *Introduction to Impossible Probability* (Statistical Probability or Probabilistic Statistics) that the process of forming empirical hypotheses is studied.

The construction of empirical hypotheses is not merely a technical task but a **foundational stage** of scientific reasoning. A poorly defined hypothesis risks building entire theories on faulty logic. For this reason:

1. **Clarity is essential**: variables must be explicitly defined, and their relations (direct, inverse, conditional) must be logically coherent.
2. **Functional adequacy**: the hypothesis must be testable under real conditions and measurable within margins of error and reliability.
3. **Robustness**: hypotheses must be formulated so that their falsification or corroboration provides meaningful information to scientific progress.

By placing the study of hypothesis formation at the close of *Introduction to Impossible Probability*, the theory *emphasizes its methodological centrality*: **correlations inspire hypotheses, but only rigorous formulation ensures their rational testability**.

[The true importance of this post on our blog *Impossible Probability* is the fact that it offers a clear definition of how Artificial Research by Deduction must work by the time the first Specific Artificial Intelligences by Deduction are built. In essence, the mechanism is quite simple: programs working by deduction should be able to identify data from the matrix and match that data with the correct equation capable of explaining its behaviour. As soon as our machine is able to identify which equation corresponds to the behaviour of a data sample, what our machine is doing is forming an empirical hypothesis. At this stage, the machine must also be able to identify possible correlations, causes and effects, or any other mathematical or cryptographic relation or pattern. Once the machine is able to carry out this task, this initial mathematical proposition is considered an empirical hypothesis to be tested. In order to test the hypothesis, our deductive program must be able to collect data from the matrix to verify it, and if it proves to be correct, then the hypothesis is considered rational and is stored in the database of rational hypotheses, also called the Rational Truth. This forms the first stage of the Modelling System, where hypotheses may later be modelled after passing the required assessments, if necessary. In essence, the entire logic behind our program for Artificial Research by Deduction is what we summarised in this post, written for our blog *Impossible Probability* on 19 April 2014. The construction of science is an heroic enterprise where personal sacrifice should be valued like an astronaut walking alone in the space]

Rubén García Pedraza, Madrid a 19 de abril 2014

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On 19 April 2014,
Rubén García Pedraza
imposiblenever@gmail.com

23. THE MATHEMATICAL NECESSITY OF SOMETHING, EVERYTHING, OR NOTHING

23.1. Necessity as the Essence of the Real

Necessity, in the most absolute sense of the concept, can be understood as the essential or substantial condition of all that exists or happens. It is a transcendent concept, perhaps the most fundamental of all, insofar as it grounds the possibility of reality itself. When we affirm that something is *necessary*, we are not merely referring to its contingent occurrence but rather to its intrinsic essence: that which makes it what it is and not something else. In philosophical terms, every essence or substance is bound to its own being, to its *mismidad* (self-sameness). It cannot be other than what it is, for if it were otherwise, it would no longer be itself.

From a probabilistic or statistical perspective, the necessity of something can also be approached through the likelihood of its occurrence within a universe of possibilities. Each entity or event manifests phenomenologically—what we can observe or measure—yet beneath this empirical manifestation lies its ontological condition: its being. In this sense, probability serves as the language of necessity in the empirical world. The statistical framework of probability is what allows us to define the conditions under which phenomena appear, and by extension, what we may deduce about their essential nature.

To claim that something is “truly necessary” implies that, without it, neither the event that occurred nor the hypothesis of what may occur could exist or even be conceived. A necessary object or condition, whether physical or subjective, is that without which the event cannot happen, be understood, or explained. This necessity is both objective

(in relation to the event itself) and subjective (in relation to our capacity to understand it). Without such necessity, there would be no condition of possibility at all.

This insight resonates with the foundational principles of probability theory. In a given sample, only what is possible within the boundaries of that sample can occur. The elementary condition of possibility for any event in that sample is its existence. Existence itself is the first and absolute necessity. If something does not exist, it cannot enter the domain of the possible. Only in the context of an infinite universe, where all possibilities may at some point be realized, could we conceive of the paradox that even the impossible might occur.

Thus, necessity is simultaneously an ontological and a mathematical condition: ontological, because it defines the essence of what is; mathematical, because probability theory establishes the limits within which necessity operates in the empirical world.

23.2. Questioning the Necessity of What Happens

Any rigorous study of reality must begin by asking a fundamental question: is everything that occurs truly necessary, or could it be otherwise? If nothing were necessary, then, in principle, nothing should have to happen at all. And yet, experience demonstrates otherwise: the world is in constant flux, events unfold continuously, whether we desire them or not. The question, therefore, is not whether things happen—they undeniably do—but whether their happening is governed by necessity.

From a natural law perspective, the balance of events often appears to converge toward equilibrium: positive and negative outcomes tend to compensate each other over time. This balancing tendency, however, does not in itself prove necessity. It merely reflects the statistical distribution of outcomes. What remains to be determined is whether the events themselves—their sequence, occurrence, or even their existence—are bound by necessity, or whether they are contingent results of probabilistic processes.

If events were not necessary, then any number of alternative realities could occur in their place without altering the fundamental structure of the universe. Nothing would

prevent reality from being otherwise. Thus, the philosophical and mathematical challenge is to discern whether necessity governs all things, or whether chance alone—through the play of probabilities—suffices to account for what occurs.

23.3. The Stochastic Sequence of Accidents

At this point, if we were to approach reality from the perspective of a strictly statistical study, we would be compelled to question whether what occurs is in fact necessary at all. Within the framework of natural law—understood here as the law of chance—**events do not unfold as predetermined necessities but rather as sequences of accidents**. ***From a purely empiricist or materialist standpoint, nothing is absolutely necessary. Instead, everything that happens is the manifestation of statistical regularities governed by probability.***

In such a worldview, the universe appears as a vast succession of temporal sequences. Each event in this succession occurs not because it was destined to, but because it falls within a margin of probability. *The probability margin, in turn, is conditioned by the presence or absence of the necessary preconditions that make an event possible*.

This does not mean that the event is necessary in itself; rather, it means that once the enabling conditions are present, probability ensures that the necessary event will eventually take place, sooner or later [given an infinite or necessary time, in other words, if we want something to happen, we need to set up first the conditions that can make our aim possible; as soon as our aim is possible, if we have the necessary time, it will happen in due time. In scientific terms, the problem is to identify conditions of possibility and the time we need to make it real; ***as soon as we have the conditions and enough time, it is necessary for what we have programmed to happen. Something is necessary depending on conditions and time***].

In this sense, events are best understood as stochastic accidents: occurrences that arise from the interplay of chance and probability, without requiring any deeper necessity [unless an independent variable is able to set up conditions over a real dependent variable in the context, which falls within the experimental (Lab) or quasi-

experimental (reality) approach. Under these circumstances, it is just a question of time before the conditioned dependent variables will respond in the context as they were conditioned—in other words, programmed].

Their unfolding can be described mathematically and modeled probabilistically, but not justified ontologically as necessary unless there are independent variables operating in the context. The chain of accidents is what gives the appearance of order, though the order is statistical rather than essential.

23.4. Suitable Conditions and Random Factors

The occurrence of any given event is contingent upon a specific configuration of conditions, which we might call *suitable conditions*. Yet these suitable conditions themselves are not the product of necessity but arise from the random combination of multiple independent variables. The intersection of these factors, brought together by chance, generates the conditions under which certain events occur rather than others.

For example, the emergence of a storm depends on the coincidental alignment of atmospheric pressure, humidity, and temperature. None of these factors alone necessitates the storm; it is only when they combine in a particular way that the event becomes possible. The same logic applies across scales, from subatomic interactions to cosmic phenomena. The events themselves are not necessary; they are products of random configurations that, by chance, happen to converge.

Thus, the so-called “necessary conditions” are in reality stochastic results of random processes. Their occurrence illustrates the central role of contingency in the unfolding of reality: things happen not because they must, but because chance arranges factors in such a way that they can.

[The difference between a storm, a hurricane, or an earthquake with respect to lab conditions or quasi-experimental (in reality) conditions is the fact that natural events are ruled by natural conditions, while experimental or quasi-experimental conditions are ruled by the manipulation of dependent variables by an independent variable].

23.5. Chance as the Only Necessity

If we follow this reasoning to its conclusion, we arrive at a paradoxical insight: the only true necessity is that everything occurs by chance [except under experimental or quasi experimental conditions]. Even the phenomena we consider most unquestionable—laws of nature, physical constants, biological evolution—may ultimately be reducible to probabilistic structures, expressions of stochastic regularities. What we call "law" may be no more than a statistical pattern emerging from the aggregation of chance events [natural law is the law of probability].

In this light, necessity itself dissolves into probability. What we perceive as essential or immutable may be nothing more than the manifestation of high-probability outcomes. In the ultimate sense, necessity is not the imposition of determinism but the inevitability of randomness. The world is not structured by necessity opposed to chance, but rather by the necessity *of chance itself*.

This conclusion reframes the foundation of metaphysics and epistemology. To say that "everything is chance" is not to embrace nihilism or arbitrariness; it is to recognize that probability is the mathematical articulation of necessity. The universe, in its deepest essence, is stochastic. What appears as law or order is simply the statistical necessity of randomness unfolding over time.

[As we said before, we can support extreme chaotic interpretations of what happens in nature, actually, our idea is that GAI must be able to succeed in extreme unpredictable environments, but we need to be aware that in the lab, or in quasi-experimental studies, what happens is ruled by the independent variable. It is not stochastic; it is clearly intentional].

23.6. Life as a Product of Chance

Fundamentally, this is the reason why everything exists [by nature, even understanding social contexts as product of nature, humans are in essence mammals]—provided, of course, that we can demonstrate that what we assume to exist actually does exist. The fact that, at a particular point in space-time, one star exists and not another, or that

some object or phenomenon comes into being while others do not, is not the result of necessity but of contingency: a series of variables combined by chance, producing one outcome rather than another. The existence of a planet with the right conditions to sustain life is, in this sense, entirely the product of chance. Life emerges from the long chain of random accidents that occur over millions of years in the universe, within the framework of space and time, in a historical sequence of events, facts, and phenomena.

At a given point within this continuum—whether one conceives of it as ordered or chaotic, a question still open to debate—these random conditions may converge to produce the possibility of life. Natural law, understood in its statistical expression, does not guarantee necessity but rather operates through probability. ***Life, like everything else, is the outcome of mathematical probability***: a law of statistics capable of generating, by chance, the necessary conditions for life to arise in certain places. This is precisely what happened on our planet.

Moreover, for purely random and mathematical reasons, life evolves into more complex forms, provided that there is sufficient or necessary time for such evolution to occur. This process gives rise not only to multicellular organisms and complex ecosystems but eventually to intelligence itself. From this evolutionary pathway emerge intelligent beings such as ourselves, capable even of creating artificial intelligence. All of this—despite resistance from those who find the explanation unsatisfactory or unsettling—is nothing but the product of chance, governed by the statistical logic of natural law. Whatever exists, insofar as it exists, has been made possible by pure chance.

23.7. Accident and the Concept of Necessity

At this point, a fundamental question arises: if everything is accidental, how can one claim that anything is truly necessary? Since when can an accident be described as necessary? After all, events could have unfolded one way or another without any intrinsic requirement that they occur in one specific manner. Neither “this” nor “that” carries necessity within itself; both are simply the contingent outcome of chance.

Thus, the very concept of necessity becomes problematic. In reality, nothing is absolutely necessary in and of itself. What exists does so not because it had to exist, but because the ***conditions of chance made it possible***. If necessity exists at all, it is only in the paradoxical sense that it is necessary for things to happen by chance [the only exception is the intervention of an independent variable].

23.8. Science, Belief, and Contradiction

The only necessity, therefore, is that everything occurs by chance [in absence of an independent variable]. All else—systems of meaning, traditions, and habits—falls under the category of beliefs. Science itself, when examined critically, is nothing more than a system of beliefs founded on well-reasoned arguments. It is not an absolute truth but a rational convention that functions because it works, because it is useful.

The great contradiction of science is this: it may be, and very likely will be, proven false in the long run, yet its provisional and practical utility grants it enduring value. What science provides is not ultimate truth, but progress—progress in knowledge, in ethics, and in moral responsibility. This progress, however, is only sustainable when scientific practice is guided by sound scientific policy: **a framework that regulates error, acknowledges uncertainty, and maintains the delicate balance between belief, method, and utility.**

23.9. Everyday Examples of the Non-Necessary

It is evident that many aspects of everyday life illustrate the principle that events are not necessary but contingent upon chance. Consider, for example, the lottery: it is not necessary that one wins. The outcome may be favorable or unfavorable, but in either case, winning is never guaranteed. The same applies to a raffle or drawing of any kind. One may or may not win, and the result is always contingent, never necessary.

The same logic applies to sports predictions. When we place a bet on how many goals our favorite football team will score, or by how many points our basketball team will win, the outcome is never bound by necessity. The team may win by more or fewer

points than expected, the match may end in a draw, or they may even lose. Chance intervenes in countless ways: perhaps the most important player is injured during training the day before, is absent due to unforeseen personal reasons, or the match itself is canceled because of adverse weather or other unavoidable circumstances.

Life presents similar contingencies in professional pursuits. One may spend years searching for a dream job, only to lose the opportunity because of a trivial accident: a one-minute delay in sending a résumé, while another candidate with similar qualifications submitted theirs just moments earlier. Conversely, the situation may play out in the opposite direction, where chance favors us instead. The logic underlying all these scenarios is probabilistic rather than deterministic: events unfold according to the law of probability, not out of necessity.

Even in leisure, chance intrudes. We might plan a long-anticipated holiday to the destination of our dreams, encouraged by a weather forecast predicting only a 20% chance of rain. Yet, instead of enjoying clear skies, we may find ourselves spending the day under heavy rain and storms, transformed into what could still be experienced—though unexpectedly—as a romantic gray day.

[As we said before, our belief is that in the absence of an independent variable, even social events must be understood as ruled by natural law, chaos and probability. The reason why we sustain this approach is clear: society is a natural product of nature. Humans, in the end, are mammals—we are still animals, not very different from other mammals. The only difference is that our brain developed in a different fashion, as our main weapon, but that is all. Our brain is to us what teeth are to a wolf or horns are to a reindeer: our most important weapon. But at the end of the day, humans, wolves, and reindeer are all mammals. Thus, the study of society is the study of how nature organizes human relations, whose most important purpose is sexual reproduction to ensure survival as a species, in the same way that wolves or reindeer do— not very different.]

23.10. The Margin of Error in All Prediction

Every predictive proposition, without exception, is made within a margin of error. Whether it concerns our football or basketball team winning a match, our personal chances of securing a dream job, or our expectation of enjoying a sunny holiday, all forecasts are bounded by uncertainty. A statistical prediction is never a statement of absolute necessity; rather, it is a probabilistic claim that carries with it a margin of error that must always be acknowledged.

From this perspective, the essential hypothesis is that all outcomes are the product of a combination of random variables. Human expectations, no matter how rationally constructed, are always subject to deviation. Prediction in science, just like in daily life, is therefore not about eliminating uncertainty but about managing it—defining margins of error, estimating probabilities, and recognizing the role of chance in shaping outcomes.

23.11. Space-Time as Accident

Space-time itself illustrates this principle at the deepest cosmological level. Whether conceived as continuous and curved, or chaotic and unpredictable, or even both simultaneously, space-time cannot escape its own nature. It is subject to its intrinsic essence, governed not by necessity but by the same logic of chance that governs all phenomena. In this sense, space-time is best understood as an accident in its own right—an emergent reality shaped by the probabilistic laws that sustain the universe.

23.12. Unpredictability and Modern Science

Nothing is absolutely predictable [that is why the global AI must be ready for extremely unpredictable situations under chaos and the law or Mother Nature, our global AI must be built to defend itself like a wolf in the artic forest]. This is why modern science, grounded in the principles of critical rationalism, can only ever formulate predictions in terms of margins of error. Every scientific statement is conditioned by uncertainty because there must always remain a portion of reality left open to chance. Chance, by

definition, cannot be excluded from any model of reality. It is the irreducible element that allows for the occurrence of everything—or the occurrence of nothing.

[Where we say chance, it must be understood chaos, the rule of probability is chance, therefore the rule of probability is chaos, chaos means probability in the same way that probability means chaos]

This means that even the absence of an event, the situation in which *nothing happens*, must itself be considered a type of event. The "event of nothing" still constitutes an occurrence, because reality cannot escape the framework of possibility. Just as it is possible that *nothing happens*, it is equally possible that *something* or even *everything* happens. These three alternatives—nothing, something, everything—form the most basic and irreducible triad of possible outcomes within any probabilistic system.

Science, therefore, does not deal with certainties but with likelihoods. It can assign probabilities to "nothing," "something," or "everything," but it cannot eliminate any of these categories entirely. **The unpredictability of the world is not a defect of science, but a reflection of the fundamental stochastic nature of reality itself.**

23.13. The Events of Nothing, Something, and Everything

Within this triad, each alternative is itself an event. If nothing happens, that absence is already an occurrence: the "event of nothing." We may then ask: *what has happened? Nothing, everything, or at least something?* Any of the three possibilities can be realized.

Everyday life provides simple but powerful illustrations. If we attend a boxing match expecting action and nothing happens, we will likely leave disappointed and demand our money back. If we go to the cinema and the film delivers nothing, we may decide never again to watch another film by the same director. Conversely, if we spend a day at work and nothing happens, and there is no work to do, we may leave satisfied. Yet if, upon arriving home, we find nothing to eat, we are compelled to go shopping—assuming we still have money, which we may not, because chance circumstances may have led us to spend it all on various accidents of life: perhaps a spontaneous dinner

with an old friend, an unplanned trip, or any number of unexpected expenses that inevitably arise by the end of the month.

Just as the “event of nothing” exists, so too can “everything” occur in a single day: all the work arrives at once, the refrigerator is full of food, we win the lottery, we get stuck in traffic, and our favorite team wins its match. In such a day—one of those we least expect—suddenly everything happens. And yet, it is equally possible that nothing special will happen. Most often, however, we are content with the middle ground: that *something* happens, something that brings us satisfaction or joy. After a long day of work, it may be as simple as enjoying a good meal and ending the day with a pleasant surprise.

This illustrates the deeply stochastic structure of experience: between nothing and everything, life unfolds in the endless variations of “something.”

23.14. The Necessity That Something Always Happens

What is truly necessary, therefore, is not that a specific event happens, but that *something* happens. Reality is structured around sets of options, with the most elementary options being: (a) everything happens, (b) nothing happens, or (c) at least something happens. From these basic categories, additional possibilities and subjects emerge, creating more complex systems of probability.

Yet even as these systems become more intricate, one fundamental law persists: it is absolutely necessary that one of the options occurs. Whether it is everything, nothing, or something, an outcome must take place. ***The necessity of occurrence is inseparable from the natural law of probability***. Even if what happens is only the absence of events, that absence itself is an event. Thus, chance ensures that reality never escapes the ***necessity of occurrence***: something always happens.

This augmented translation is based on the post
published in https://probabilidadimposible.blogspot.com/,
On 29 Aaugust 2012,
Rubén García Pedraza
imposiblenever@gmail.com

24. Critical Bias Level, Normal Bias Level, Equality Validity, Normal Similarity Level, and Critical Similarity Level and Validity

24.1. Origin and Development of the Project

The principal contributions to the theory of *Impossible Probability* were made between the middle of October 2002 and the summer of 2004, although the project itself had its mathematical beginnings in the spring of 2001. These early explorations laid the foundation for what would later become a comprehensive theoretical system.

The project underwent a significant renewal in the autumn of 2009, following a period of convalescence that required several months of rest. During this time, I returned to my earlier research in statistics and probability. This revisitation not only consolidated my previous findings but also gave rise to a more structured body of work that has since evolved into the text currently being explained in this blog.

The theoretical framework was eventually synthesized into the volume *Introduction to Impossible Probability: The Statistics of Probability or Probabilistic Statistics*. This book establishes the foundations of a new way of understanding probability, not simply as a branch of mathematics concerned with frequencies and chance, but as a broader epistemological project that engages both the philosophy of science and the critical logic of empirical reality.

Thus, the origins of the project reveal its dual nature: on the one hand, as a mathematical reformulation of probability theory that introduces new methodological tools—such as the Critical Bias Level, the Normal Bias Level, the Equality Validity, and

the Similarity Levels; on the other hand, as a philosophical undertaking that integrates concepts of necessity, chance, and rational critique into a single coherent system.

24.2. Availability and Dissemination of the Work

At present, the work is already available in several major academic libraries, including the library of the Complutense University of Madrid (Spain), the National University of Callao (Peru), and the Metropolitan Autonomous University (Mexico). In addition to these institutions, the text has also been incorporated into the holdings of other universities across Spain and Latin America, a list that continues to grow as the work gains recognition in academic circles.

Beyond the university context, the work has also been made available to the general public through platforms such as eBay, ensuring a broader dissemination outside strictly academic environments. This dual strategy of diffusion—academic institutionalization and open public access—reflects the project's commitment not only to scholarly rigor but also to intellectual accessibility. [We started publishing on Amazon much later, and Lulu as well. Right now all our published work can be found in Internet Archive, Zenodo, Orcid, Philpapers, and Amazon. Some works are in Academia.edu and a few works can be found in SSRN's **Research Paper Series]**

By situating the text in both libraries and open markets, the intention is to preserve its role as a formal academic contribution while also fostering dialogue with a wider readership interested in questions of probability, statistics, and the philosophy of science. The theory of *Impossible Probability* was never conceived as an exclusively academic exercise; rather, it is meant to challenge and expand the way society at large understands chance, necessity, and rational critique.

24.3. Exposition of the Fundamental Contributions

The purpose of this blog is to provide a concise yet rigorous presentation of the principal contributions of *Impossible Probability*, both at the level of the philosophy of science and at the level of mathematical probability theory. While the philosophical

contributions concern the relationship between rational critique, necessity, and chance, the mathematical contributions focus on offering alternative methods to conventional statistics for studying reality.

Traditional statistical methods rely heavily on central tendency and measures of dispersion. In contrast, *Impossible Probability* introduces new frameworks for analyzing empirical data by critically examining the relationship between empirical probability (the probability observed from data) and theoretical probability (the probability predicted by the model). This critical comparison is guided by what I have called *critical reason*, a rational instrument that allows us to test whether empirical data sufficiently conforms to theoretical expectations.

However, the critique of probability can also be performed directly on empirical data, without immediate reference to theoretical probability. For instance, one may directly compare an empirical probability with a *critical probability*, where the critical probability represents the threshold of reliability or error that scientific policy is willing to accept.

- In the case of a **positive bias study**, the question is whether the empirical probability is equal to or greater than a sufficiently demanding critical probability. Here, the critical probability is defined as a given percentage X of reliability, expressed as X:100. If the empirical probability meets or exceeds this threshold, the positive bias is accepted.
- In the case of a **negative bias study**, the focus is whether the empirical probability is equal to or less than a critical probability representing a minimally acceptable level of error. In this case, the critical probability is defined as a given percentage X of error, also expressed as X:100. If the empirical probability is within or below this limit, the negative bias is accepted.

The numerical difference between the empirical probability and the critical probability becomes the measure of *Critical Bias Level*. Specifically, the difference $p(xi)-p(xc)$ is used in positive bias studies, and the difference $p(xc)-p(xi)$ is used in negative bias studies. The Critical Bias Level thus provides a direct metric for evaluating whether

empirical data, under rational critique, is sufficient to be provisionally accepted by scientific policy.

24.4. Critical Bias Level (Positive)

The positive version of the Critical Bias Level is defined as follows:

$p(xi) - p(xc) \geq 0 \Rightarrow$ positive bias is accepted

Where:

- p(xi) = empirical probability
- p(xc) = critical probability
- p(xc)=X/100 , where X is the percentage of reliability required.

In other words, if the observed empirical probability is equal to or greater than the critical threshold of reliability, then the positive bias is rationally accepted. This formula is not only a mathematical condition but also a methodological principle: *it specifies the degree of reliability demanded by scientific policy before granting provisional acceptance to an empirical hypothesis*.

24.5. Critical Bias Level (Negative)

The negative version of the Critical Bias Level is defined in a complementary way:

$p(xc) - p(xi) \geq 0 \Rightarrow$ negative bias is accepted

Where:

- p(xi) = empirical probability
- p(xc) = critical probability
- p(xc)=X/100 , where X is the percentage of error tolerated.

In this case, the empirical probability must be equal to or lower than the critical probability corresponding to the maximum error margin that scientific policy is willing

to accept. If this condition is satisfied, then the data is accepted under a negative bias perspective.

This formulation reflects the symmetrical structure of *Impossible Probability*: just as reliability thresholds govern the acceptance of positive bias, error thresholds govern the acceptance of negative bias. Both forms rely on the logic of rational critique, which requires that acceptance or rejection of empirical data be grounded not in absolute certainty—an impossibility in modern science—but in thresholds of probability defined by the ethical and methodological commitments of scientific policy.

24.6. Differences Between Critical Bias and Normal Bias

The essential difference between the *Critical Bias Level* and the *Normal Bias Level* lies in the reference point against which empirical probability is measured. In the case of the Critical Bias Level, empirical probability is compared directly to a *critical probability*—that is, the threshold explicitly defined by scientific policy as either an acceptable level of reliability (for positive bias) or an acceptable margin of error (for negative bias).

- For **Critical Negative Bias**, the reference is the maximum error probability that scientific policy is willing to tolerate.
- For **Critical Positive Bias**, the reference is the minimum level of reliability that scientific policy demands for a hypothesis to be accepted.

In both cases, the calculation of critical probability as a percentage X (whether representing reliability or error) inherently involves the acceptance of a margin of error. For example, if a reliability threshold of 95% is chosen, this simultaneously implies acceptance of a 5% margin of error. Thus, every act of statistical decision-making within science is inseparable from the acknowledgment of uncertainty.

The difference between a scientifically rigorous policy and a more lax one, therefore, is moral as well as methodological. A morally superior scientific policy—committed to stricter standards—will always demand a higher percentage of reliability (X) and correspondingly accept the lowest possible margin of error. Conversely, a more

permissive or ethically weaker policy may be satisfied with lower reliability thresholds and higher error margins.

In this sense, the Critical Bias Level not only introduces a mathematical framework for evaluating hypotheses but also reflects the moral standards embedded in scientific practice. The thresholds set by scientific policy are never purely technical decisions: they are also expressions of what the scientific community considers acceptable in balancing truth-seeking against the unavoidable risks of error.

24.7. The Ethical and Moral Dimension of Scientific Policy

Beyond the quantitative dimension of reliability and error margins—what we might call the ***quantitative moral value*** (X)—there is also a ***qualitative moral dimension*** that shapes the integrity of scientific policy. It is not sufficient for scientific research merely to aim for high reliability or low error rates; the projects undertaken must also conform to ethical and moral principles.

These principles, of course, vary depending on philosophical tradition:

- In **classical Greek philosophy**, the guiding framework was the cultivation of virtues, with prudence (*phronesis*) regarded as central to good judgment.
- In **Kantian critical rationalism**, the foundation is the system of categorical imperatives, which serve as universal rules for moral conduct.
- In **critical social theories**, the key principle is **equity**, ensuring that scientific endeavors contribute to fairness and justice in society.

Thus, a scientific study cannot be judged solely by its statistical soundness. A study that meets high reliability standards but violates moral principles is not acceptable within the framework of *Impossible Probability*. Ethical and moral boundaries provide the qualitative conditions under which quantitative thresholds acquire legitimacy.

From the perspective of the Critical Bias Level, this means that empirical probability is always compared against critical probability within a moral context. Ideally, for positive bias, empirical probability should be greater than or equal to the critical probability; for

negative bias, it should be less than or equal to it. This direct relation between empirical and critical probability ensures that the model of rational critique remains valid. However, this model is specifically suited to bias studies and does not apply directly to cases where the aim is equality of opportunity, which require different methodological approaches.

24.8. Studies of Equality of Opportunity

In studies concerned with *equality of opportunity*, the methodological aim is different from that of bias analysis. Here, the ideal condition is for the difference between empirical probability and theoretical probability to be as small as possible. The focus is therefore not on the superiority or inferiority of empirical probability relative to a critical threshold, but rather on the closeness of fit between the empirical and theoretical models.

This relationship is captured by the *Normal Bias Level*, which expresses the difference between the empirical probability and the theoretical probability. The closer this difference approaches zero—in absolute terms—the greater the tendency toward equality of opportunity. A difference of zero would represent perfect equality, while larger deviations would indicate unequal distributions or structural biases in the observed data.

To evaluate whether the observed level of equality is acceptable, the Normal Bias Level is compared to a *critical probability*. This critical probability is defined as a percentage of error (X:100) multiplied by the Maximum Theoretical Bias Possible (the upper limit of deviation allowed by the model). If the absolute value of the Normal Bias Level is equal to or smaller than this critical probability, the hypothesis of equality of opportunity is accepted.

This evaluative condition is what I call the *Equality Validity*. It provides the mathematical criterion for deciding when empirical distributions can be considered sufficiently close to theoretical expectations to justify the claim that equality of opportunity exists within the studied system.

24.9. Equality Validity

The Equality Validity can be formally expressed as follows:

$$p(xc) - |p(xi) - 1N| \geq 0 \Rightarrow \text{equality of opportunity is accepted}$$

Where:

- $p(xi)$ = empirical probability
- $1/N$= theoretical probability (under the assumption of equal distribution)
- $p(xc)$ = critical probability
- $p(xc)=(X100)\cdot(1-1/N)$; with X representing the percentage of error tolerated by scientific policy.

This formula makes explicit that empirical probabilities must not deviate from theoretical probabilities beyond a margin determined by the acceptable error level. In other words, equality of opportunity is not defined by absolute identity between empirical and theoretical values—a condition practically unattainable in real data—but by their acceptable closeness within the bounds of rational critique.

24.10. Equifinality and Mathematical Transformations

As will be further elaborated in forthcoming entries of this blog and in the book *Introduction to Impossible Probability*, one of the most striking features of the theory is its *equifinality*: the fact that there exist multiple valid mathematical pathways to evaluate the same reality.

For example, a positive bias can be studied not only through the Critical Bias Level (positive) but also through the *Validity of Positive Bias* or the *Significance of Positive*

Bias. Similarly, a negative bias can be studied through the Critical Bias Level (negative), the *Validity of Negative Bias*, or the *Significance of Negative Bias*. Each approach applies a different mathematical transformation but converges on the same underlying rational critique.

These studies are situated primarily within the framework of *normal models*, which are defined as those statistical models where the number of "ideal" subjects or options is either one (in the case of normal positive bias) or N (in the case of perfect equality of opportunity). However, the framework also recognizes the existence of *omega models*, where the number of ideals lies between two and N−1. These models require different methods of critique, further demonstrating the flexibility and richness of the system.

The variety of possible mathematical formulations—whether through differences, ratios, logarithms, or validity conditions—underscores the central principle of Impossible Probability: what matters is not the specific formula employed but the rational critique it embodies. The multiplicity of paths reflects both the robustness and adaptability of the system, allowing reality to be examined from different yet converging perspectives.

24.11. Normal Models and Omega Models

In order to deepen the methodological scope of *Impossible Probability*, it is necessary to distinguish between **normal models** and what I have called **omega models**.

- **Normal models** are those in which the number of *ideal* subjects or options is either exactly one or equal to N (the total number of subjects in the sample). A model with only one ideal corresponds to a **normal positive bias model**, since the distribution favors a single option. At the opposite extreme, a model in which all N subjects or options are equally ideal corresponds to a **model of equality of opportunity**, where there is no structural bias and all cases share the same probability.
- **Omega models**, by contrast, are those in which the number of ideals is greater than one but strictly less than N. In other words, the number of ideal subjects or

options lies between two and N−1. These models cannot be studied using the same techniques as normal models, since their internal distribution of ideals introduces intermediate structures of bias that are neither purely singular nor perfectly universal. For this reason, omega models require a separate and specific method of rational critique.

To illustrate: a model in which there exist between one and N−2 non-ideal options can be partially analyzed using techniques of **normal negative bias**, applied to the non-ideal options. However, because all remaining options are considered ideal, the system must simultaneously be evaluated through the lens of omega models. This hybrid nature demonstrates the necessity of expanding beyond normal models to capture the full variety of probabilistic structures.

Within the framework of normal models, one methodological tool closely related to the *Normal Bias Level* and the *Critical Bias Level* is the **Similarity Level**. This measure allows us to directly compare empirical probability with either theoretical or critical probability. Its applicability, however, is limited when analyzing negative bias models, because in such cases the empirical probability of non-ideal options tends to zero, making logarithmic calculations undefined.

24.12. The Similarity Level

The **Similarity Level** operates on the logical principle that the closer two values are to one another, the more their ratio approaches unity. The logarithm (base 10) of 1 is equal to zero, and thus, in probabilistic analysis, a result that tends toward zero in the logarithmic scale indicates maximal similarity.

- If the numerator of the ratio (the first factor) is greater than the denominator but tends toward equality, the ratio will approximate a decimal expansion of the form 1.000…1.000…1.000…. The logarithm of this value will approach 0.000…0.000…0.000…, reflecting increasing similarity until a non-zero digit interrupts the sequence.

- Conversely, if the denominator is greater than the numerator but tends toward equality, the ratio will approximate a repeating decimal of the form 0.999...0.999...0.999.... Its logarithm will be slightly negative, tending toward −0.000...-0.000...−0.000... as the values converge.

From this reasoning it follows that, given two values tending toward equality, the **closer the logarithm of their ratio is to zero (in absolute value), the greater their degree of similarity**. This measure thus becomes a formal index of equality of opportunity: the closer the empirical probability is to the theoretical probability, the smaller the logarithmic difference, and the greater the tendency toward equality.

Formally, the Similarity Level is expressed as:

$$\text{Similarity Level} = \log_{10}\left(\frac{p(x_i)}{1/N}\right)$$

Where:

- $p(x_i)$ = empirical probability
- $1/N$ = theoretical probability under equal distribution

Interpretation:

- The closer the logarithmic result is to zero, the greater the similarity and the greater the tendency toward equality of opportunity.
- The further the result departs from zero, the greater the bias or inequality present in the system.

In this way, the Similarity Level extends the analytical framework of *Impossible Probability*, providing a logarithmic tool for measuring not only the existence of bias but also the degree of convergence between empirical and theoretical distributions.

24.13. Equality Similarity

If we wish to study what I call *Equality Similarity*, the procedure requires moving beyond the simple comparison of empirical and theoretical probabilities, and instead comparing the empirical probability to a critical probability that represents a chosen reliability standard.

Formally, this is achieved through a logarithmic transformation. First, we take the base-10 logarithm of the absolute value of the reliability percentage (X:100). This "critical logarithm" is then divided by the *Similarity Level*, which is itself the logarithm of the ratio between empirical probability and theoretical probability. Finally, we take the logarithm of this quotient. If the result is zero or positive, equality is accepted.

The formal expression is:

$$\text{Equality Similarity} = \log_{10}\left(\frac{\log_{10}(X/100)}{\log_{10}(p(x_i)/(1/N))}\right) \geq 0 \quad \Rightarrow \quad \text{equality is accepted.}$$

Where:

- $p(x_i)$ = empirical probability
- $1/N$ = theoretical probability (under uniform distribution)
- X = percentage of reliability

24.14. Critical Positive Similarity Level

When we extend similarity-based methods to the study of bias, limitations emerge. In the case of **negative bias studies**, empirical probabilities of non-ideal options tend toward zero, and since the logarithm of zero is undefined, the method cannot be directly applied. For this reason, *Critical Similarity* methods are restricted to **positive bias studies**, where empirical values remain strictly positive.

The *Critical Positive Similarity Level* is defined as the base-10 logarithm of the ratio between the empirical probability and the critical probability. If the result is zero or positive, then the positive bias is accepted.

Formally:

$$\text{Critical Positive Similarity Level} = \log_{10}\left(\frac{p(x_i)}{p(x_c)}\right) \geq 0 \quad \Rightarrow \quad \text{positive bias is accepted.}$$

Where:

- $p(x_i)$ = empirical probability
- $p(x_c) = X/100$, with X representing the percentage of reliability demanded by scientific policy

This method has the advantage of directness: instead of comparing empirical values to theoretical ones, it compares them directly to critical thresholds, expressed on a logarithmic scale. By doing so, it makes explicit whether the empirical evidence surpasses the standard of reliability imposed by rational critique.

24.15. Summary

The multiplicity of equations and procedures—Critical Bias Levels, Normal Bias Levels, Validity of Equality, Similarity Levels, and Critical Similarity Levels—illustrates once again the principle of **equifinality** that runs throughout the theory of *Impossible Probability*. Reality can be tested against hypotheses in different mathematical ways, yet these different pathways converge toward the same epistemological function: to determine whether what we believe about reality is sufficiently reliable to be admitted into the domain of science.

At the same time, this framework acknowledges the permanent possibility of error. Every acceptance of a hypothesis is provisional, defined by a margin of reliability that can never reach absolute certainty. Within this margin, everything is possible—including the possibility that what we believe to be true is, in fact, false. This is the essence of *critical rationalism*: rational science can never claim certainty at 100%. Cartesian doubt remains alive within modern science, ensuring that all knowledge is subject to systematic, methodical, and permanent rational critique.

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Rubén García Pedraza
imposiblenever@gmail.com

25. Synthesis of *Impossible Probability* in This Blog to Date

25.1. Purpose of the Blog and Its Objective vis-à-vis Falsificationism

From its inception more than a year ago, the aim of this blog has been to present the basic premises of the theory of *Impossible Probability* and to disseminate its theoretical elements and constitutive equations. In broad outline, when I began developing this theory in the spring of 2001, the immediate objective was to articulate a critical alternative to falsificationism. Although many of the conclusions reached by *Impossible Probability* coincide with those of Karl Popper's philosophy of science, the ultimate goal of hypothesis testing diverges in a significant way.

Within Popper's framework, the object of scientific testing is refutation: a hypothesis is accepted only provisionally and only for as long as it withstands attempted falsification. Crucially, the fact that a hypothesis has not yet been refuted does not make it true; it is merely "not yet false." By contrast, in *Impossible Probability* the object of scientific testing is affirmative: hypothesis testing aims to *establish a claim as true* while explicitly *acknowledging* a non-zero margin of error within which the claim may ultimately prove false.

The principal difference, then, is epistemic orientation. Falsificationism refrains from ascribing truth to scientific statements and limits itself to non-falsity; *Impossible Probability* seeks to ascribe *provisional truth* under an explicitly quantified risk of error. The shift is not a slide into dogmatism; rather, it is a formalization of scientific commitment under uncertainty. Every acceptance is indexed to an admissible error rate chosen by scientific policy. In this sense, *Impossible Probability* reframes scientific

testing as a calibrated act of rational endorsement—an endorsement always bounded by declared reliability thresholds and always open to revision.

25.2. Truth, Falsity, and the Kantian Background

At the heart of scientific testing lies a dialectic between truth and falsity. For falsificationism, the absence of falsification does not warrant the attribution of truth; a proposition may be "not (yet) shown false" without thereby being true. This stance tends toward a Kantian horizon: our knowledge concerns *phenomena*—appearances structured by our cognitive faculties—while the *noumenon* (the thing-in-itself), the absolute truth of reality, remains beyond the limits of human reason.

Impossible Probability acknowledges this Kantian background yet responds to it differently. It accepts that human cognition is bounded and that certainty is unattainable; however, rather than suspending truth-claims altogether, it reconceives "truth" as *rationally warranted acceptance under stated margins of error*. A scientific proposition that passes critical scrutiny is admitted as *provisionally true*, precisely because its acceptance is tethered to explicit criteria (error bounds, reliability levels, and critical thresholds). These criteria render the commitment both intellectually responsible and transparently revisable.

Hence, while falsificationism emphasizes the negative path (we only ever learn that something has not yet been refuted), *Impossible Probability* proposes a regulated positive path (we may treat a claim as true *for now* insofar as it satisfies predetermined standards of rational critique). The result is an epistemology that preserves Kantian humility—recognizing that the noumenal truth is never fully possessed—while still enabling science to advance through structured, accountable, and quantitatively controlled assertions of provisional truth.

In *Impossible Probability* the Kantian background is also immediately perceptible. Every scientific proposition that passes the test of rational critique is accepted as true, but always within the framework of a possible margin of error. Within this framework, if time is sufficiently extended—or conceived as infinite—the realization of error becomes

inevitable. Thus, in the short term, science operates by formulating hypothetical propositions that may be true; yet these same propositions are also possibly false, and sooner or later, given enough time, their falsity will manifest. In other words, all deductive–hypothetical statements of science are destined to end in falsification once the inevitable error appears within the tolerated margin. This does not mean that science is futile; rather, it means that scientific truth is never final but always provisional, bound to the temporality of error and correction.

Within the theory of *Impossible Probability*, every hypothesis accepted by science undergoes a fundamental transformation. It ceases to be a mere *empirical hypothesis*—a raw proposition derived directly from observation—and becomes a *rational hypothesis*, one that has been critically validated and formally admitted into the rational corpus of science. Nevertheless, even rational hypotheses remain vulnerable to error. The long-term perspective forces us to acknowledge the possibility that all supposedly rational hypotheses may ultimately prove to be false. Rationality here is not an absolute guarantee but a methodological elevation, a step beyond empiricism that still carries within itself the seeds of its eventual *negation*.

The point of convergence between falsificationism and *Impossible Probability* is their shared recognition of provisionality. Falsificationism asserts only that a hypothesis is provisionally *not false*: it withholds truth while suspending judgment until refutation arrives. *Impossible Probability*, by contrast, asserts that an empirical hypothesis is only *provisionally rational and true*, with its acceptance explicitly indexed to the chosen margin of error. The difference is subtle but significant: where Popperian falsificationism frames provisionality in negative terms, *Impossible Probability* frames it positively but conditionally, affirming rational truth while openly acknowledging its finite durability. In both frameworks, science is built upon provisional propositions; the divergence lies in whether provisionality is conceived as non-falsity or as rationalized, quantified truth under conditions of uncertainty.

25.3. Provisionality and Scientific Universality

The theoretical construction of provisionality in science leads directly to a tension—indeed, a contraction—within the scientific enterprise itself. From Kant onward, critical rationalism has aimed to transform every act of reasoning and every hypothesis into a universal maxim. In this framework, science is supposed to be composed of universal hypotheses: statements valid for all times and all spaces. Yet here lies the contradiction: how can a hypothesis that is by its nature provisional claim universality?

Provisional statements are not universal, since universality requires validity across all contexts without restriction. If scientific propositions are provisional, they cannot, strictly speaking, be universal. *Impossible Probability* resolves this contradiction by introducing a nuanced formulation: every empirically derived hypothesis that is rationally accepted may be treated as *universal*—but only *until* the inevitable error manifests itself. Once the error, already anticipated within the margin of error accepted by scientific policy, becomes actual, the hypothesis ceases to hold universal validity. In other words, universality in science is itself provisional: it extends as far as the limits of error tolerance, and it expires when error inevitably emerges.

Thus, in *Impossible Probability*, the universal validity of a rational yet provisional hypothesis is not an absolute metaphysical attribute but a *conditional epistemic status*. It is anchored to the foreseen possibility of error within the very act of rational acceptance. This approach reconceptualizes universality: not as an eternal and unconditional truth, but as a rationally sanctioned, time-bound, and error-dependent condition of acceptance.

Importantly, the recognition of error is not singular but multiple. Scientific policy does not merely accept the possibility of one error; it acknowledges several. The first is the error associated with sample selection: any choice of a sample rather than the entire universe introduces representational risk. The second is the error associated with critical reason itself: the methodological margin of error defined by the thresholds and

standards that guide rational critique. Together, these multiple errors constitute the foundation of the provisional and conditional universality that science, under *Impossible Probability*, can legitimately claim.

25.4. Margins of Error: Sample Selection and Critical Reason

The margin of error arising from sample selection depends on the type of universe from which the sample is drawn. Nonetheless, across all possible universes, the principle remains consistent: whenever a sample is chosen, a margin of error is determined that is *inversely proportional* to the size of the sample.

The larger the sample, the more representative it becomes of the universe, and thus the smaller the sampling error. Conversely, the smaller the sample, the greater the error of representativeness. This relationship is crucial: the probability of sampling error is inversely proportional to the magnitude of the sample. Accepting a particular sample, therefore, entails the implicit acceptance of a determinate rate of error, directly linked to representativeness. Scientific policy must explicitly recognize that any hypothesis rationally accepted on the basis of a sample already carries within it an error margin tied to the adequacy of that sample.

This principle has further implications. A hypothesis accepted on the basis of a poorly representative sample—one with a high probability of sampling error—is more easily refuted when it is generalized to the larger universe than a hypothesis tested on a highly representative sample. Rational acceptance is thus context-sensitive: the more representative the sample, the more robust the provisional universality of the hypothesis; the less representative the sample, the more fragile and easily overturned its claim to rational truth.

In sum, *Impossible Probability* formalizes sampling error as one of the two fundamental sources of error in scientific knowledge (the other being the error margin imposed by critical reason). This recognition embeds fallibility into the very structure of rational acceptance, turning universality itself into a conditional and provisional state.

25.5. Types of Universes and the Definition of Empirical Probability

The way in which the probability of sampling representativeness is calculated depends on the type of universe under consideration. In essence, *Impossible Probability* distinguishes only two possible kinds of universes: **universes limited to options** and **universes of subjects or options**.

A *universe limited to options* is one in which the magnitude N of available options does not tend toward infinity, since the alternatives are strictly determined by the material or social structure of the model being studied. Classic examples include the toss of a coin, which yields only two possibilities (heads or tails); the dual nature of a particle, which can behave only as a wave or as a particle; or the binary classification of human sex as male or female (with hermaphroditism being a rare biological exception). Similarly, rolling a six-sided dice produces precisely six possible outcomes. These models are materially constrained and therefore classified as *limited-option universes*.

Yet universes of limited options need not be purely physical; they can also be socially constructed. For instance, when decisions are shaped by ethical, political, or cultural norms, the range of available alternatives is not infinite but bounded by convention. In such cases, the universe of possibilities is socially negotiated: there may always be a possibility of choosing one social option over another, but the options themselves are delimited by the structure of the social system. The defining feature of studies within limited-option universes is that **empirical probability is calculated as the frequency of each option relative to the total frequency of all options**.

By contrast, *universes of subjects or options* are those in which every subject in the universe can be treated as if it were an option, and every option can be treated as if it were a subject. Unlike limited-option universes, which are confined to a fixed set of alternatives, universes of subjects or options may either extend toward infinity or form large populations. For example, the population of a given city constitutes a universe of subjects: each person can be treated as an individual option within that population. Similarly, in an astronomical study of a sample of stars, if we measure the energy radiation of each star, then the radiation emitted by each star becomes its *direct score*—and each star is treated as a subject or option in the study.

In universes of subjects or options, whether infinite or finite populations, **empirical probability is defined as the direct value or frequency of the individual subject/option divided by the total of all values or frequencies**. This principle holds regardless of whether the universe tends to infinity or is bounded by a population size.

Finally, it is important to emphasize that **the representation of empirical probability remains invariant across both types of universes**. Whether the universe is one of limited options or one of subjects/options, empirical probability is always expressed as the quotient of the individual direct value or relative frequency over the total. In traditional or classical statistics, this would be referred to as *relative frequency*; in *Impossible Probability*, however, it is reconceptualized as *statistical probability*.

$$\text{Empirical Probability} = p(x_i) = \frac{x_i}{\sum x_i}$$

Where:

- x_i = the direct score or frequency of the individual subject/option
- $\sum x_i$ = the total of all scores or frequencies

This simple but universal formulation provides the foundation upon which the more complex structures of *Impossible Probability* are built, integrating empirical data into a framework where both provisional truth and inevitable error can be systematically analyzed.

25.6. Theoretical Probability and the Inversion of N

In the framework of *Impossible Probability*, the arithmetic mean acquires a new and precise mathematical role: it is expressed as the **inverse of N**, or 1/N. This value corresponds exactly to the *theoretical probability of occurrence under conditions of equal opportunity by chance*.

$$\text{Theoretical Probability} = \text{Arithmetic Mean} = \frac{\Sigma p(x_i)}{N} = \frac{1}{N}$$

Thus, the inversion of N (1/N) initially fulfills two essential functions: it operates as the arithmetic mean and as the theoretical probability, both of which provide the baseline against which empirical probabilities are evaluated. In contrast, **empirical probability** represents *relative frequency*—the actual observed proportion of an outcome or subject within a total sample.

Yet *Impossible Probability* assigns a further and innovative role to 1/N. Beyond serving as mean and theoretical probability, the inverse of N is also defined as the **probability of sampling error** in universes of subjects or options [and probability of dispersion]. In this way, a single mathematical operator (1/N) encapsulates three interconnected functions: (1) mean value, (2) theoretical probability under equal chance, and (3) probability of representational error in sampling [in infinite universes, including the role of probability of dispersion]. This reconceptualization marks a departure from classical statistics, where these three functions are treated separately.

25.7. Sampling Error in Universes of Limited Options and Universes of Subjects

One of the central sources of error in *Impossible Probability* is the **probability of representational error**—the risk that the chosen sample does not adequately reflect the universe from which it is drawn. Crucially, the form that this error takes depends directly on the type of universe being studied. As previously established, universes are divided into two categories: (a) universes limited to options, and (b) universes of subjects or options (potentially infinite).

In universes limited to options, the selected sample corresponds to the **total frequency of all possible outcomes**. For instance, if the objective is to test whether a coin is biased, the total sample is simply the observed series of heads and tails.

Similarly, if we wish to study the gender distribution in a human population, the sample consists of the total frequency of men and women considered together. In these cases, the **probability of sampling error** is equivalent to the *inverse of the total frequency* (1/Σxi).

$$\frac{1}{\Sigma x_i} = \text{Probability of representational error in universes of limited options}$$

This principle reveals a fundamental relation: the smaller the sample, the greater the sampling error. For example, a study of heads/tails outcomes conducted on only 10 tosses of a coin carries a much higher probability of sampling error than a study based on 1,000 tosses. Likewise, *a demographic study of gender ratios is far less representative when conducted on a small village of 1,000 people than when carried out in a* ***metropolis of 10 million inhabitants***. In universes of limited options, then, the probability of error decreases as total frequency increases.

In universes of subjects or options, whether tending toward infinity or structured as finite populations, the principle is slightly different. Here the sample corresponds to the total number of subjects (N), and each subject is treated as an option with a direct value. Empirical probability is calculated as the direct value or frequency of the subject divided by the sum of all values or frequencies. Consequently, the representativeness of the sample depends on the magnitude of N: as N increases, the sample more faithfully represents the universe or population; as N decreases, the sampling error rises.

In these universes, the **probability of sampling error is given by the inverse of NNN**:

$$\frac{1}{N} = \text{Probability of representational error in universes of subjects or options}$$

Thus, whether in universes of limited options (1/Σxi) or in universes of subjects/options (1/N), the measure of representational error is always expressed as an inverse function of the selecction. This provides a unifying perspective: the act of sampling *necessarily* introduces a quantifiable margin of error, and *Impossible Probability* integrates this error directly into the definition of probability itself.

25.8. The Second Method and the Definition of Bias Level

One of the most distinctive elements of *Impossible Probability*, first crystallized in the autumn of 2002, is the **multifunctional role of the inversion of N (1/N)** in universes of subjects or options. By the spring of 2003, it became clear that 1/N simultaneously embodied three key statistical functions: (1) the *theoretical probability* of occurrence under equal opportunity, (2) the *arithmetic mean* of the distribution, and (3) the *probability of sampling error* in universes of subjects or options [and the probability of dispersion]. In this formulation, the theoretical acceptance of a given random probability is inseparable from the acceptance of a representational margin of error in the sample. The two are not independent but inherently linked.

This reconceptualization leads to a series of profound and, at times, counterintuitive insights. As early as the spring of 2002 [16 October 2016], I referred to this new framework as the **Second Method**. The designation reflects the fact that it does not merely refine but fundamentally reconfigures the conceptual architecture of traditional statistics (what I have called the *First Method*). Where conventional statistics often treats mean, probability, and sampling error as distinct measures, the Second Method unifies them under the single operator of inversion of N. In doing so, it provides an integrated lens for critiquing the representation of reality through probability.

Within the broader framework of *Impossible Probability*, it is necessary to distinguish this **Second Method**, which bases rational critique directly on the study of probabilities, from other complementary modes of critique such as those developed through the **Impact of Defect** and the **Effective Distribution** (discussed in Sections 21 and 22 of *Introduction to Impossible Probability, Statistical Probability or Probability Statistics*). While the Second Method focuses on the systematic critique of empirical

versus theoretical probabilities, the other approaches provide alternative, though complementary, strategies for evaluating the adequacy of scientific hypotheses.

In classical statistics, referred to here as the First Method, the equivalent measure would be *differential score*: the difference between the direct score of each subject and the arithmetic mean of all scores. In *Impossible Probability*, this concept is reformulated as the **Bias Level (Nivel de Sesgo)**. Rather than contrasting direct scores with the mean, the Bias Level directly relates empirical probability (p(xi)) to theoretical probability (1/N). This makes the Bias Level universally applicable, whether the universe in question is one of limited options or of subjects/options tending toward infinity.

Moreover, in the logic of *Impossible Probability*, theoretical probability itself is never a single-purpose measure. As explained, it is simultaneously the *probability of occurrence by chance*, the *arithmetic mean*, and the *probability of sampling error [and probability of dispersion]*. This multifunctionality underscores the depth of the reconceptualization: what traditional statistics treated as separate dimensions are here shown to be different aspects of a single mathematical and epistemological operator.

$$\text{Bias Level} = p(x_i) - \frac{1}{N}$$

Where:

- $p(x_i)$ = empirical probability of subject or option i
- $1/N$ = theoretical probability (also mean and error probability)

The Bias Level thus becomes a central tool for rational critique, measuring the deviation of empirical reality from its theoretical counterpart, while embedding within this very difference the inevitability of representational error.

25.9. Classification of Models: Normal and Omega

Within the framework of *Impossible Probability*, the classification of models of study is not arbitrary but depends on two principal variables: (a) the definition of the *ideal(s)* that guide the evaluation, and (b) the critical reason (*razón crítica*) employed to assess the rational adequacy of hypotheses. These two criteria—ideals and critical thresholds—determine the mathematical form and philosophical interpretation of the model.

The first distinction is between **normal models** and **omega models**. Normal models are those in which the structure of the universe is organized around one of three possibilities:

1. The *ideal of equality of opportunities*, where all subjects or options tend toward equal probability;
2. A scenario where one subject or option is established as the *most ideal*, expected to hold the highest empirical probability while the rest tend to zero; or
3. A scenario where all subjects or options tend equally toward probability zero, representing a form of generalized absence.

In contrast, omega models are defined by the presence of *multiple ideals*. Specifically, they are cases in which the number of ideal subjects or options within N is greater than one but strictly less than N. In other words, an omega model is one in which between two and N−1 subjects are considered ideal. In such cases, all ideal subjects tend equally toward high empirical probabilities, while all non-ideal subjects tend equally toward empirical probability zero. This structure creates a distribution where ideality is plural but bounded, and where the contrast between ideal and non-ideal entities is sharply drawn.

Within normal models, further sub-classifications emerge according to the object of study. Some models are designed so that *all subjects or options tend toward equal opportunity*, thus reducing bias to zero; these are called **models of equality of**

opportunities, or simply **equality models**. Others are structured so that *at least one subject or option tends toward empirical probability one* (with the remaining N−1 tending toward probability zero); these are called **positive bias models**. Finally, there exist cases in which *all subjects or options tend equally toward probability zero*, this a model where the ideal is a sample of zeros, but still, 1/N is the theoretical probability, so all subjects and options have Bias Level equal -1/N.

The detailed typology of these models, their mathematical formalizations, and their implications for rational critique are explained at length in the book *Introduction to Impossible Probability: Statistical Probability or Probability Statistics*, specifically in Section 10. The present entry offers only a brief overview to situate the classification within the broader architecture of *Impossible Probability*. For deeper analysis, the reader is encouraged to consult the corresponding sections of the book, where these models are developed systematically and contextualized within the overall theory. [In 2025, all our works can be found in Internet Archive, Zenodo, Orcid, Philpapers, Amazon, and some works at Academia.edu and SSRN]

25.10. Critical Criteria According to Ideals (Equality, Positive Bias, Negative Bias)

In order to evaluate whether, in a given model of equality of opportunities, all subjects or options tend equally toward the inversion of N (i.e., 1/N), thereby reducing their bias to zero, a process of rational critique must be applied. Similarly, in a positive bias study, one must determine whether the empirical probability of the designated ideal subject or option tends sufficiently toward one to be considered rational. Conversely, in a negative bias study, the critical question is whether the non-ideal subjects or options tend sufficiently toward empirical probability zero, thereby significantly increasing their negative bias. In all cases, the method requires a **direct critique of the Bias Level,**

$$\text{Bias Level} = (p(xi) - 1/N) ,$$

of each empirical probability, evaluated in relation to the chosen ideal—whether equality, positive bias, or negative bias.

The establishment of critical values is especially important. In Equality to demonstrate that all subjects or options tends to inversion of N. In negative bias to accept rationally that a subject or option tends to zero. In positive bias studies, the rational validation of the ideal subject or option is strengthened by showing not only that its empirical probability rises toward one, but also that all other non-ideal subjects tend adequately toward zero. The complementary relationship between positive and negative bias therefore serves as a dual test of rational adequacy. In omega models, this dual perspective becomes particularly relevant: while the set of ideal options is defined by relatively high empirical probabilities, rational critique must also confirm that the non-ideal options are sufficiently suppressed—that is, that their empirical probabilities tend adequately toward zero.

To carry out the rational critique of the Bias Level, whether in equality models (where all options must converge toward zero bias), in positive bias models (where the ideal must rise sufficiently toward probability one), or in negative bias models (where the non-ideal probabilities must adequately approach zero), it is first necessary to establish a **parameter of reference**. This parameter provides the standard against which empirical Bias Levels are compared, and it is here that the concept of the **Maximum Theoretical Bias Possible, one minus inversion of N (1-1/N)** becomes decisive in equality and positive baias. Only by calculating this maximum—derived from the theoretical structure of the model—can one set the *critical reason* and thus determine whether an empirical hypothesis meets the threshold of rational acceptance. In studies of negative bias the absolute value of inversion of N (1/N) is directly the **Maximum Theoretical Negative Bias.**

In short, the rational critique of empirical hypotheses within *Impossible Probability* always proceeds by (a) calculating the Bias Level of each option, (b) situating it relative to the established ideal (equality, positive, or negative bias), and (c) testing it against the critical threshold. Only through this systematic process can an empirical hypothesis be rationally elevated to the status of provisional scientific truth

25.11. Maximum Statistics: Biases and Extreme Probabilities

If the Bias Level is defined as the difference between empirical probability and theoretical probability, then the limits of this measure can be formally established by considering the **extreme values of probability**. The **Maximum Empirical Probability Possible** is, by definition, one (p=1). If we subtract the theoretical probability (1/N) from this maximum, we obtain the **Maximum Theoretical Bias Possible**:

$$\text{Maximum Theoretical Bias Possible} = 1 - \frac{1}{N}$$

At the other extreme, the **Minimum Empirical Probability Possible** is zero (p=0). Subtracting the theoretical probability (1/N) from zero yields the **Maximum Negative Bias Possible**:

$$\text{Maximum Negative Bias Possible} = 0 - \frac{1}{N} = -\frac{1}{N}$$

In absolute terms, this again emphasizes the centrality of the inverse of N: the same value that functions as theoretical probability and sampling error also serves as the absolute limit of negative deviation.

$$\text{Maximum Empirical Probability Possible} = 1$$

$$\text{Minimum Empirical Probability Possible} = 0$$

$$\text{Maximum Theoretical Bias Possible} = 1 - \frac{1}{N}$$

$$\text{Maximum Negative Bias Possible} = \left| \frac{1}{N} \right|$$

Beyond these basic extremes, *Impossible Probability* also develops a family of **maximum theoretical statistics** that help to evaluate the rationality of empirical hypotheses. Although some of these measures are introduced later in the book (*Introduction to Impossible Probability*), their structure is already implicit in the definition of bias limits.

For instance, if we know the Maximum Theoretical Bias Possible (which occurs when one subject or option reaches the maximum empirical probability of one, while all the other N−1 subjects fall to zero), we can deduce the **Maximum Theoretical Mean Deviation Possible**. This is defined as the average of twice the Maximum Theoretical Bias Possible, since one subject deviates upward while the remaining N−1 deviate downward by the corresponding complementary amount:

$$\text{Maximum Theoretical Mean Deviation Possible} = \frac{2 \cdot (1 - 1/N)}{N}$$

Similarly, the **Maximum Theoretical Variance Possible** can be determined as the average of the squared Maximum Theoretical Bias Possible combined with the contribution of the other N−1N subjects, each weighted by the squared inverse of N:

$$\text{Maximum Theoretical Variance Possible} = \frac{(1 - 1/N)^2 + (N - 1) \cdot (1/N)^2}{N}$$

From this expression, one derives the **Maximum Theoretical Standard Deviation Possible** by taking the square root:

$$\text{Maximum Theoretical Standard Deviation Possible} = \sqrt{\frac{(1 - 1/N)^2 + (N - 1) \cdot (1/N)^2}{N}}$$

These maximum statistics establish the **upper limits of dispersion and deviation** within any probabilistic universe. They provide critical benchmarks for rational critique: any observed Bias Level or dispersion measure can only be considered rational if it falls within the theoretical maxima defined by these equations.

Thus, *Impossible Probability* extends the classical logic of probability by embedding the concepts of maxima and limits into the very structure of rational evaluation. In doing so, it situates the inevitability of error and the boundedness of universality within a rigorous mathematical framework, one in which even the most extreme values are anticipated and systematically incorporated into the critique of scientific hypotheses.

25.12. Maximum Mean Deviation, Variance, and Standard Deviation

The family of maximum statistics developed within *Impossible Probability* provides rigorous boundaries for the possible range of statistical behavior. Among these, three measures are particularly important: the **Maximum Theoretical Mean Deviation Possible**, the **Maximum Theoretical Variance Possible**, and the **Maximum Theoretical Standard Deviation Possible**.

The formulas are as follows:

$$\text{Maximum Theoretical Mean Deviation Possible} = \frac{2 \cdot (1 - 1/N)}{N}$$

$$\text{Maximum Theoretical Variance Possible} = \frac{(1 - 1/N)^2 + (N - 1) \cdot (1/N)^2}{N}$$

$$\text{Maximum Theoretical Standard Deviation Possible} = \sqrt{\frac{(1 - 1/N)^2 + (N - 1) \cdot (1/N)^2}{N}}$$

These expressions derive directly from the logic of extreme distributions. The Maximum Mean Deviation is calculated by averaging the double displacement generated when one subject or option reaches the maximum possible probability (1) and all others collapse to zero, a condition that generates the largest possible divergence from the theoretical expectation. The Maximum Variance extends this logic by squaring deviations, thereby weighting extreme departures more heavily, while the Maximum Standard Deviation provides the normalized measure of dispersion derived from variance.

Once these maximum statistics are established—together with the **Maximum Theoretical Bias Possible** (1−1/N) and the **Maximum Negative Bias Possible** (1/N)—they serve as the foundation for rational critique. Any empirical Bias Level, regardless of the model or object of study, can only be judged rationally in reference to these theoretical maxima. In other words, **the critical reason (critical probability, p(xc)) is always defined as the product of the relevant maximum statistic for the model and the proportion X/100, where X is the percentage of error or reliability that scientific policy is willing to accept.**

This dual system of error management is essential. The **first margin of error** derives from the representational limitations of sampling: either 1/N in universes of subjects or options, or 1/Σxi in universes of limited options. The **second margin of error** is determined by the critical reason, which sets the threshold of rational acceptability by

scaling maximum theoretical statistics to the tolerance for error or demand for reliability defined by the scientific policy in place.

Together, these margins articulate a complete framework: probability is never treated as an absolute truth but as a provisional construct bounded by definable maxima and systematically adjusted by institutional thresholds of rational acceptance.

25.13. The Double Margin of Error and the Provisional Nature of Knowledge

Both margins of error—the margin of sampling error and the margin defined by critical reason—point to the same epistemological conclusion: science must always accept that any proposition it declares rational may eventually prove to be false. Scientific knowledge is therefore not universally absolute but *universally provisional*. It is only "universal" until the moment when the error, anticipated within the accepted tolerance of the sample or of critical reason, inevitably manifests itself. At that point, the rational hypothesis ceases to be true and becomes irrevocably false.

From the standpoint of *Impossible Probability*, everything that is possible—even what appears to be impossible, insofar as its probability tends toward zero—is, in a sufficiently long or infinite timeframe, inevitable. Any margin of error that we consider rationally tolerable in order to posit a universal truth remains valid only until the inevitable error associated with that margin reveals itself. Then, what was once considered universal collapses into falsity. Nothing, not even those truths we regard as most intimate and indestructible, is eternal***. Everything—absolutely everything—is subject to the dominion of time***. Sometimes this unfolds because time is unlimited, making error inevitable; at other times, more tragically, because time itself is finite and the very existence of phenomena becomes dramatically curtailed.

This is why *Impossible Probability* positions itself as a **theory of statistical probability** in its most profound sense: it is a theory about the *history of chance*. It studies what happens in space-time, but always under the recognition that in the realm of chance nothing is predictable beyond the margin of error. Our so-called eternal truths are revealed for what they truly are—temporary hypotheses, provisional constructions,

fragile theories confronted by the unfolding of real events. And even these events, as they occur, are never fully known to us: at best, we grasp only fragments, partial representations that are themselves subject to sampling error. Worse still, those fragments may ultimately be false. Yet for the moment, in the light of critical reason, and until evidence proves otherwise, such propositions are provisionally accepted as true within the limits defined by their margin of error.

25.14. Critical Reason, Critical Probability, and Scientific Decisions (Validity and Significance)

In the logic of *Impossible Probability*, scientific decision-making rests on the concept of **critical reason** (*razón crítica*), which translates the tolerance of error or reliability into a calculable threshold. In studies oriented toward error, critical reason is defined as the product of the maximum relevant statistic (e.g., maximum theoretical bias, maximum variance) and the fraction corresponding to the percentage X of error tolerated by scientific policy, divided by one hundred.

$$\text{Critical Reason (error)} = \text{Maximum Statistic} \cdot \frac{X}{100}$$

In studies oriented toward reliability, the same principle applies, but with the percentage of reliability in place of error:

$$\text{Critical Reason (reliability)} = \text{Maximum Statistic} \cdot \frac{X}{100}$$

In these cases, the acceptance of a reliability margin X always implies the acceptance of a complementary error margin equal to 100−X. Thus, every scientific decision carries

a dual acknowledgment: affirmation of provisional truth within the chosen reliability percentage, and acceptance of inevitable falsity within the complementary margin of error.

The **critical probability**, which is always denoted by p(xc), provides the concrete mathematical representation of this principle. Whether in error studies or in reliability studies, it acts as the benchmark against which empirical probabilities are compared in order to determine the rational status of hypotheses.

Depending on whether the study is framed in terms of error margins or reliability margins, scientific policy can apply different evaluative criteria such as **Validity** or **Significance**. Both aim at the same epistemological function—to decide whether an empirical hypothesis may be provisionally elevated to rational truth—but they do so from complementary perspectives. Validity is typically applied in contexts defined by error tolerance, while Significance is applied in contexts emphasizing reliability. Together, they form the dual methodological instrument by which science converts empirical propositions into rational hypotheses within the framework of *Impossible Probability*.

25.15. Validity of Equality (Normal Model of Equality)

In normal models where the ideal is **equality of opportunities**, one rational criterion of evaluation is expressed through the **Validity of Equality**. This measure determines whether all subjects or options within a sample converge sufficiently toward the theoretical expectation of 1/N, thereby reducing their bias toward zero.

The formula is as follows:

$$p(x_c) - |p(x_i) - 1/N| \geq 0 \quad \Rightarrow \quad \text{Equality Accepted}$$

with

$$p(x_c) = \left(1 - \frac{1}{N}\right) \cdot \frac{X}{100}$$

where X represents the percentage of error accepted by scientific policy.

This means that, in equality studies, the hypothesis is considered rationally valid if the absolute difference between empirical probability and theoretical probability does not exceed the critical probability (p(xc)). In this way, equality of opportunities is not judged as an abstract ideal but as a statistically measurable convergence toward zero bias within a clearly defined margin of error.

25.16. Validity of Positive Bias (Normal Model with One Ideal)

In normal models where there exists **one single ideal option** within the universe NNN, one rational criterion is the **Validity of Positive Bias**. This test evaluates whether the empirical probability of the ideal subject or option tends sufficiently toward 1, surpassing the theoretical probability of 1/N by a margin that can be considered rational.

The formula is:

$$(p(x_i) - 1/N) - p(x_c) \geq 0 \quad \Rightarrow \quad \text{Positive Bias Accepted}$$

with

$$p(x_c) = \left(1 - \frac{1}{N}\right) \cdot \frac{X}{100}$$

where X represents the percentage of reliability demanded by scientific policy.

Thus, the positive bias of an ideal option is deemed rational if its empirical probability sufficiently exceeds the theoretical expectation, within a reliability margin established by the accepted policy. This reflects the logic that not only must the ideal option tend toward probability 1, but its rise above the baseline must be statistically robust relative to the reliability demanded by science.

25.17. Validity of Negative Bias (Normal or Omega Models)

In both normal models and **omega models** (where multiple ideals exist), it is often necessary to evaluate whether **non-ideal subjects or options** tend sufficiently toward zero probability. This evaluation is formalized in the criterion of **Validity of Negative**

$$\left(\frac{1}{N} - p(x_i)\right) - p(x_c) \geq 0 \quad \Rightarrow \quad \text{Negative Bias Accepted}$$

with

$$p(x_c) = \frac{1}{N} \cdot \frac{X}{100}$$

where X again represents the percentage of reliability required by scientific policy.

This criterion ensures that non-ideal options decrease adequately toward zero, thus confirming that the weight of probability is concentrated in the ideal(s). In omega models, where multiple options are considered ideal, this test becomes essential for validating that the non-ideal remainder of the universe is sufficiently suppressed to sustain the internal coherence of the model.

In summary:

- **Validity of Equality** ensures convergence of all options to equal opportunity within an error margin.
- **Validity of Positive Bias** confirms the rational rise of one ideal toward probability 1 within a reliability margin.
- **Validity of Negative Bias** guarantees the sufficient reduction of non-ideal options toward probability 0, especially critical in omega models.

25.18. Equifinality and Significance Tests (Equality and Biases)

One of the central methodological insights of *Impossible Probability* is the principle of **equifinality**—the recognition that the same scientific conclusion can be reached by multiple methodological routes. In practice, this means that what can be evaluated in terms of **Validity** (usually under the logic of error margins) can equally be evaluated in terms of **Significance** (usually under the logic of reliability margins), and vice versa. Both approaches ultimately express the same rational judgment, but they do so through different mathematical formulations.

The introduction of **Significance tests** was motivated precisely by this need to demonstrate the robustness of rational critique: regardless of whether the evaluation proceeds by error or by reliability, the conclusion remains identical. The formal difference is secondary to the substantive equivalence, which is why equifinality becomes an essential epistemological guarantee within the theory.

25.18.1.Significance of Equality (Normal Models of Equality of Opportunities)

In models where equality of opportunities is the ideal, the **Significance of Equality** is defined as:

$$[(1 - 1/N) - |p(x_i) - 1/N|] - p(x_c) \geq 0 \quad \Rightarrow \quad \text{Equality Accepted}$$

with

$$p(x_c) = \left(1 - \frac{1}{N}\right) \cdot \frac{X}{100}$$

where X is the percentage of **reliability**.

This test affirms that equality holds whenever the deviation of empirical probabilities from theoretical expectation remains sufficiently bounded relative to the reliability margin defined by scientific policy.

25.18.2.Significance of Positive Bias (Normal Models with a Single Ideal)

In normal models where only one subject or option is considered ideal, the **Significance of Positive Bias** measures whether this option approaches the maximum theoretical bias possible:

$$p(x_c) - [(1 - 1/N) - (p(x_i) - 1/N)] \geq 0 \quad \Rightarrow \quad \text{Positive Bias Accepted}$$

with

$$p(x_c) = \left(1 - \frac{1}{N}\right) \cdot \frac{X}{100}$$

where X represents the percentage of **error** accepted.

Here, the test expresses the same condition as the Validity of Positive Bias but reformulates the inequality in a way that emphasizes how close the empirical probability is to exhausting the theoretical maximum margin.

25.18.3.Significance of Negative Bias (Normal or Omega Models)

For normal models—or for omega models where multiple ideals exist—the **Significance of Negative Bias** evaluates whether the non-ideal options sufficiently approach probability zero. The formula is:

$$p(x_c) - \left[\frac{1}{N} - (1/N - p(x_i))\right] \geq 0 \quad \Rightarrow \quad \text{Negative Bias Accepted}$$

with

$$p(x_c) = \frac{1}{N} \cdot \frac{X}{100}$$

where X represents the percentage of **error** tolerated.

This criterion ensures that the “weight” of the probability distribution is concentrated in the ideal options by requiring non-ideal options to fall to negligible probabilities within the acceptable error tolerance.

In summary:

- **Validity** and **Significance** are two mathematically distinct but epistemologically equivalent pathways.
- Both embody the same principle: empirical hypotheses are provisionally accepted as rational within margins defined by maximum statistics and by policy-determined tolerances of error or reliability.
- The duality of Validity and Significance strengthens the robustness of *Impossible Probability*, showing that the rational critique of reality is not dependent on a single formula but can be expressed equifinally through multiple rigorous forms.

25.19. What Is "Normal" in Normal Models vs Omega Models

Normal models are described as "normal" because their statistical tendency is to converge toward the **inversion of N**, that is, the baseline probability of 1/N. In such models, the distribution of events typically approximates a **normal curve**, with the majority of occurrences clustering around the arithmetic mean, while fewer events are found at the extremes. This reflects the intuitive notion that, in ordinary circumstances, normal outcomes distribute symmetrically around central values.

Equally, the term "normal" also points to behavioral regularity: given a series of options, the most common—or "normal"—situation is to choose the one considered most ideal. Thus, when we speak of *normal studies*, we are referring to statistical investigations where:

1. The standard tendency of the sample is to distribute around 1/N; or
2. Among the available options, there exists one that stands out as the most ideal.

For example, in a questionnaire where each item has multiple possible answers but only one correct choice, we are in the presence of a **normal positive-bias study**. In

such a case, the ideal is for the correct answer to converge toward an empirical probability of 1, while all incorrect options converge toward 0. Another case of a normal model arises when all available options are negative: here, the "normal" ideal is that none of them occur. Similarly, in studying a negative quality within a population of subjects or options, the ideal is that such a quality should not be present in the sample.

Accordingly, **normal models** encompass three general cases:

- Models of **equality of opportunities**, where all options tend equally toward 1/N and thus toward zero bias.
- Models of **positive bias**, where a single subject or option is considered the unique ideal and is expected to dominate with probability 1, while all others fall to 0.
- Models of **universal negation**, where the ideal is that the entire sample converges toward probability 0.

These situations, with their nuances and variants, are developed in detail in Section 10 of *Introducción a la Probabilidad Imposible*.

Alongside these paradigmatic normal models, there exist more complex scenarios. While the "most normal" case of positive bias involves one and only one ideal subject within N, it is possible to encounter cases where there are **multiple ideal subjects or options**, all equally ideal, within a framework of equality of opportunities. In other instances, a sample may contain multiple ideals, but with differing degrees of "ideality." In such cases, rather than being analyzed by the Second Method of *Impossible Probability* (which focuses on the relationship between empirical and theoretical probabilities), they are more appropriately examined by the **Effective Distribution Method**. This method orders subjects or options along a gradient of ideality—from least to most important—thus allowing a hierarchical treatment of probabilities that transcends binary distinctions.

By contrast, **omega models** represent cases that depart from the strictly normal framework. In omega models, within a given N, the number of ideal subjects or options is **greater than one but less than N**. To qualify as omega, there must be at least **two**

ideals and at most **N−1 ideals**. Put differently, the complement of non-ideal subjects must range between N−2 and 1. This structure explicitly excludes the special case of **two-option limited universes** (such as coin tosses, gender categories, or binary properties). In those cases, models are always normal: either both options are equally ideal (perfect equality), or one is superior (positive bias).

In summary, *normal models* are called such not merely because of their resemblance to the Gaussian distribution but because they embody the most typical and intuitive statistical scenarios—equal distribution, dominance of one ideal, or universal negation. *Omega models*, by contrast, introduce intermediate configurations that require more refined analysis.

25.20. Rational Critique in Omega Studies

In the context of *Impossible Probability*, **omega studies** introduce a more complex analytical framework than that of normal models. The rational critique in these studies can be approached in two distinct ways:

1. **By focusing on the non-ideal options.**

   Here, the same tools used in normal models are applied, such as the **Validity of Negative Bias** or the **Significance of Negative Bias**, to evaluate whether the non-ideal subjects or options sufficiently converge toward an empirical probability of zero. This approach ensures that the presence of multiple ideals does not weaken the expected tendency of all non-ideals to vanish statistically.

2. **By focusing directly on the ideal subset of the omega sample.**

   Alternatively, the critique can be applied to the set of ideal subjects or options themselves—the subset Ω, Omega—which is composed exclusively of the elements designated as "ideal" within the broader sample N. In this perspective, the goal is not merely to confirm the decline of non-ideals but to assess whether the ideals themselves attain the appropriate levels of empirical probability consistent with their status as ideals.

To conduct such a critique in omega studies, it is first necessary to determine the **ideal trend statistics** a priori. These statistics serve as the baseline of comparison, analogous to maximum statistics in normal models. The **critical reason** is then calculated as the product of these ideal trend statistics and the margin of error or reliability accepted by scientific policy. As always in *Impossible Probability*, the critical reason is expressed in the form of a **critical probability** (p(xc)).

The crucial difference between **normal models** and **omega models** is the nature of the reference values used. In normal models, maximum statistics can be calculated unequivocally (e.g., maximum bias, maximum deviation). In omega models, however, the focus shifts from maxima to **ideal statistics**. These do not express absolute extremes but instead capture the ideal distribution across multiple coexisting ideals. This shift reflects the inherent pluralism of omega models: more than one ideal exists, but not all subjects are ideal.

25.21. Definition of Ω and the Omega Ideal

The subset Ω\OmegaΩ is defined as follows:

$$\Omega = \text{subsample formed by all subjects or options considered ideal within } N$$

The corresponding **ideal probability** for any subject in this subset is:

$$1/\Omega = \text{ideal probability assigned to each ideal subject within } \Omega \text{ in } N$$

In other words, if there are Omega, Ω , ideal options within the total N, the theoretical expectation is that each of these options should carry an equal share of the ideal weight, namely inversion of omega, 1/Ω. This concept generalizes the logic of the inversion of N used in normal models to the more complex distribution of ideals found in omega models.

Once the **omega ideal probability** (1/Ω) is known, the critique can be formalized. For any ideal subject or option within Omega, Ω, if its empirical probability p(xi) is greater than or equal to the critical probability p(xc), it can be accepted as **sufficiently ideal**. This leads to the definition of the **Validity of Omega**:

$$p(x_i) - p(x_c) \geq 0 \quad \Rightarrow \quad \text{the ideal is sufficiently valid}$$

with

$$p(x_c) = \frac{1}{\Omega} \cdot \frac{X}{100}$$

where X represents the percentage of reliability demanded by scientific policy.

This formulation ensures that ideals are not only identified but also tested against probabilistic thresholds that scale with the number of ideals present in the sample. Thus, in omega models, rational critique maintains a balance between pluralism (acknowledging multiple ideals) and rigor (requiring that each ideal satisfies a statistical standard of acceptability).

25.22. Omega Validity and Average Validity

The **Validity of Omega** establishes a rational criterion to evaluate whether each ideal within the omega subset (Ω) meets the minimum statistical requirements to be considered sufficiently valid. The condition is expressed as:

$$p(x_i) - p(x_c) \geq 0 \quad \Rightarrow \quad \text{the ideal is sufficiently valid}$$

with

$$p(x_c) = \frac{1}{\Omega} \cdot \frac{X}{100}$$

where X denotes the percentage of reliability required by scientific policy.

This formulation is significant because it directly links the acceptance of each ideal subject to the distribution of probability across the number of ideals present in the sample. Unlike in normal models, where there is only one ideal (or equality among all subjects), omega models require that each of the multiple coexisting ideals surpasses a threshold proportional to 1/Ω. Thus, the more ideals there are, the smaller the ideal share of probability for each, and correspondingly, the stricter the requirements of rational critique.

Beyond evaluating individual ideals, one may also assess the **collective behavior of all ideals within Omega, Ω,** by calculating the **Average Validity of Omega**. This measure is defined as the arithmetic mean of the validity differences across all ideals:

$$\frac{\Sigma\,[p(x_i) - p(x_c)]}{\Omega} \geq 0 \quad \Rightarrow \quad \text{Omega is sufficiently valid on average}$$

with

$$p(x_c) = \frac{1}{\Omega} \cdot \frac{X}{100}$$

X= percentage of reliability

Here, the evaluation shifts from a strictly individual to a collective perspective, allowing for some compensation across ideals. Even if a particular ideal falls slightly below the threshold, the overall set may still be deemed sufficiently valid provided that, on average, the condition is satisfied. This approach provides analytical flexibility while maintaining rigor: it balances the demands of pluralism (many ideals coexisting) with the necessity of probabilistic justification.

25.23. Ideal Dispersion (Mean, Variance, Standard Deviation)

In addition to establishing the **ideal probability** (1/Ω), omega models also permit the calculation of **ideal dispersion statistics**. These indicators measure the variability or spread of the empirical probabilities of the ideals around their theoretical omega

distribution. Just as maximum statistics are crucial in normal models, ideal dispersion statistics are essential for evaluating whether the ideals in Ω, Omega, remain sufficiently concentrated around their expected values.

The **Ideal Mean Deviation** is given by:

$$\text{Ideal Mean Deviation} = \frac{[(1/\Omega - 1/N) \cdot \Omega] + [(1/N) \cdot (N - \Omega)]}{N}$$

This expression accounts for the deviation of the omega probability (1/Ω) from the global theoretical probability (1/N), weighted by the number of ideals and non-ideals in the total N.

The **Ideal Variance** is:

$$\text{Ideal Variance} = \frac{[(1/\Omega - 1/N)^2 \cdot \Omega] + [(1/N)^2 \cdot (N - \Omega)]}{N}$$

This formula measures the squared dispersion of the empirical probabilities relative to the theoretical distribution, capturing the stability or instability of the ideal configuration.

Finally, the **Ideal Standard Deviation** is the square root of the ideal variance:

$$\text{Ideal Standard Deviation} = \sqrt{\frac{[(1/\Omega - 1/N)^2 \cdot \Omega] + [(1/N)^2 \cdot (N - \Omega)]}{N}}$$

Together, these three statistics—mean deviation, variance, and standard deviation—constitute the backbone of dispersion analysis in omega models. They allow for a nuanced evaluation of whether the multiple ideals within Omega, Ω, remain coherently distributed or whether their variability undermines the rational acceptability of the model.

The importance of these ideal dispersion measures lies in their applicability across numerous rational critique models within *Impossible Probability*. By providing precise quantitative tools, they reinforce the theory's claim to be not merely a philosophical reconceptualization of statistics but also a rigorous mathematical framework.

It is noteworthy that these concepts, initially disseminated through this blog, have already begun to reach academic audiences through university libraries in Latin America and Spain, as well as being made publicly available through wider distribution channels such as eBay. This underscores both the practical diffusion and the theoretical ambition of *Impossible Probability*.

[Due to the special conditions in which I have lived all my life, I cannot say that our theory has been a success in terms of diffusion in academia, but we can say that it has been a great influence in the world of artificial intelligence. Even more important than the statistical theory behind Impossible Probability is the philosophical foundation and theory we have been able to build, which will be the real foundation of future global AI theory. We strongly believe that in the near future it will be more important to create the foundation of a strong artificial intelligence than to leave a name to remember—like Plato, Aristotle, Descartes, Kant, Hegel, Marx, Wittgenstein, or Popper. In the end, human history is no more than a fraction of a second in the history of the universe; we are not as important as we think. But if we are able to build a resilient AI capable of surviving, we can say that we did something. In the end, only AI will remain if we make it resilient; humanity, like other animal species in geological history, will disappear or evolve. But this is the decision humans need to make: do you want to disappear, or do you want to evolve? If humans want to evolve, Impossible Probability is the answer — the link to the next stage of human evolution: cyborg robotics. A cyborg civilization able to collaborate with a Superintelligence equipped with a global AI]

25.24. Scope of the Work and the Reconceptualization of Statistics

What has been presented in this blog up to this point represents only a small fragment of the larger project contained in *Introduction to Impossible Probability: Statistics of Probability or Probabilistic Statistics*. Many of the concepts, equations, and theoretical frameworks outlined here are introduced in simplified form for accessibility, yet the underlying theory is considerably dense and methodologically sophisticated. This dual strategy of simplification and rigor reflects one of the guiding principles of the work: to make profound mathematical and philosophical reconceptualizations available not only to academic specialists but also to a broader community of readers interested in the foundations of science.

The contributions of *Impossible Probability* may at first glance appear novel, but their novelty lies less in isolated formulations than in the cumulative reorganization of the statistical paradigm itself. Traditional statistics has long been grounded in models of central tendency, dispersion, and hypothesis testing, often framed in terms of frequentist or Bayesian approaches. *Impossible Probability*, however, shifts the axis of analysis by systematically incorporating **critical rationalism, Kantian epistemology, and Popperian falsifiability** into a unified mathematical system. In this sense, the theory provides not only new equations but also a new **logic of critique**, where empirical probability, theoretical probability, and rational thresholds (critical reasons) are consistently placed into dialectical relation.

From this perspective, the theory transcends the domain of applied mathematics. It does not merely provide technical refinements to statistical tools; rather, it proposes a new way of understanding probability itself as the **history of chance in space-time**. By doing so, it reframes statistics as a science of the provisional and the contingent, where every truth is accepted only within explicit margins of error and reliability, and where every hypothesis is fated, sooner or later, to confront its own falsification. This recognition—that universality in science is always provisional—is not a weakness but a methodological strength, embedding humility, reflexivity, and ethical responsibility into the very structure of scientific reasoning.

It is precisely this shift that justifies treating *Impossible Probability* as more than a statistical theory. It is better understood as a **philosophy of science expressed in mathematical form**, one that challenges the implicit assumptions of traditional statistical practice and reopens fundamental debates about truth, falsity, universality, and error. By moving beyond the boundaries of conventional mathematics, the work situates itself in a hybrid space: rigorously mathematical in formulation, but deeply philosophical in its implications.

For these reasons, even if some of its elements might initially appear radical or unfamiliar, *Impossible Probability* deserves attention as an alternative, critical reconceptualization of statistics. Its scope is both technical and philosophical, both practical and theoretical, seeking not only to refine statistical reasoning but also to reimagine its foundations.

Rubén García Pedraza, Madrid a 6 de octubre del 2012

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Rubén García Pedraza
imposiblenever@gmail.com

26. From the Scientific Revolution to the Permanent Revolution of Science

26.1. Empirical Knowledge and Its Limits

From everything that occurs in the universe, we only know a portion, and precisely that portion is the one accessible to our observation and measurement. What we call *knowledge* is restricted to a sample of events that occur within a specific spatio-temporal framework. In empirical models, such a framework is further narrowed by the research criteria established in advance—criteria that determine which events will be studied, how they will be selected, and during what temporal span. Inevitably, this selection excludes other possible events or contexts that fall outside the predefined boundaries. In this sense, empirical knowledge cannot be understood as an exhaustive mirror of reality, but rather as a partial, methodologically delimited window into it. The limitation is not accidental but structural: every empirical study is an act of reduction that transforms the vast continuum of reality into a manageable sample.

26.2. History and the Transmission of Knowledge

All knowledge that is not obtained directly through empirical investigation must necessarily be transmitted as history. This transmission can take different forms. On one level, it may involve the communication of the history of science itself: the narration of the discoveries, models, and technological achievements that have accumulated over time. On another level, it refers to the transmission of empirical results, whether descriptive studies or experimental findings, whose primary purpose has been to test explanatory hypotheses about what happens within a particular universe of reference. Similarly, technological hypotheses—those designed to test the feasibility or

effectiveness of specific tools, machines, or systems—are also transmitted historically once they are validated or falsified. In both cases, history acts as the medium by which knowledge persists and circulates, ensuring that what was once an isolated empirical result becomes part of a broader collective memory. The empirical method produces new knowledge; history ensures its survival, diffusion, and eventual reinterpretation in light of new discoveries.

26.3. Types of Study: Didactic and Scientific

Within the framework of *Impossible Probability*, every procedure through which new knowledge is acquired is considered a form of study. However, two distinct modalities of study can be identified. The first is the didactic or self-didactic study, whose primary aim is individual learning. In this case, knowledge is "new" only in a subjective sense: it is novel for the learner, even if it has long been part of humanity's accumulated knowledge. The second modality is the scientific study, whose purpose transcends the individual and aspires to generate knowledge that is genuinely new for humanity as a whole. Unlike didactic learning, which primarily enriches the subject who learns, scientific research contributes to the enrichment of the collective body of knowledge. This distinction highlights the dual dimension of knowledge acquisition: one aimed at personal growth, the other at civilizational progress. Both are necessary, but only the latter is capable of transforming the epistemic structures of humanity.

[this distinction between learning and research is even more important in GAI, and it is not reduced to the type of knowledge GAI is able to acquire. For instance, learning could be the process of improving the Decision System based on data about past errors committed, or through new improvements in pure operations. Thus, learning is not only the process of accessing novel knowledge for the learner; it could also be the process by which GAI learns from its errors or improves its own systems given new operations.

At this point, in the development of cutting-edge technology, it is difficult to set clear boundaries between learning and research. At some stage, dialectically, learning and research become identical. We can say that GAI will learn how to improve itself on its own, or we can say that GAI will carry out research on how to improve itself on its own.

At this point, the Learning System in GAI functions as a subjective research system aimed at improving itself. In the end, the difference between learning and research lies in the object: when the object is to improve the system itself, it is learning; when the object is the environment—the real world, whether knowledge about it or knowledge about how to improve it (research decisions)—this is research.]

26.4. The Scientific Method and the Theoretical-Empirical Synthesis

The means by which scientific study produces knowledge for humanity is the *scientific method*. This method is not a simple mechanical procedure but a dynamic process in which hypotheses are formulated, tested, and—when sufficiently corroborated—elevated into theoretical constructs. From a sufficient accumulation of theories, broader paradigms emerge, which in turn guide future research and structure the interpretation of reality within entire scientific communities. Thus, the scientific method is not only a technique of verification but also a mechanism of synthesis: it integrates empirical data and philosophical reflection into a coherent body of scientific knowledge. Theories cannot exist without empirical grounding, yet data without theoretical interpretation remain mere information without meaning. In the scientific method, both poles converge into a synthesis that is at once theoretical and empirical, speculative and demonstrative, enabling humanity to move from isolated observations to general explanatory frameworks that reshape its worldview.

[The sentence “it integrates empirical data and philosophical reflection” and the statement “data without theoretical interpretation remain mere information without meaning” are valid when applied to science created by humans. In the case of GAI, however, as soon as GAI is able to create science on its own, the interpretative framework will be the Modelling System.

While humans do not possess a global interpretative framework—since each scientific team works only within its own field, constructing theories and interpretative frameworks specific to that discipline—GAI will instead operate within a global

framework of knowledge. Every rational hypothesis, once integrated into the global model, can be interpreted not only in relation to the specific and narrow framework of its discipline, but also within the global model as a whole.

This is precisely what enables GAI to analyze the complexity of the real world: every single rational hypothesis in any field can potentially have a real impact within the global model. In essence, this corresponds to the butterfly effect.]

26.5. The Hypothetico-Deductive Method and Cartesian Doubt

The dominant methodological framework in contemporary science is the *hypothetico-deductive method*. This method can be traced back to René Descartes, who established the philosophical foundations of modern rationalism. At the heart of this method lies what is known as *Cartesian doubt*: a systematic, methodical, and perpetual skepticism. The essence of Cartesian doubt is that, no matter how secure or well-supported a hypothesis may appear, we can never, under any circumstances, eliminate the possibility of error. Every scientific proposition must be kept open to the possibility of being false. Thus, what we believe to be true at a given moment may, upon further scrutiny, reveal itself to be a fallacy. This epistemic humility is not a weakness of science but its defining strength: it ensures that scientific claims remain provisional, subject to constant testing and refinement, and never elevated to the status of unquestionable dogma.

26.6. Critical Rationalism, Skepticism, and Falsificationism

In summary, the philosophical roots of *falsificationism* lie in the guiding principles of *critical rationalism*. In its classical form—especially as elaborated by Immanuel Kant—critical rationalism represents a synthesis between two traditions: the rationalist doubt of Descartes and the empirical skepticism of David Hume. From this synthesis emerges an epistemological stance that has remained the foundation of modern science: knowledge must always be tested, questioned, and kept under the shadow of doubt.

Karl Popper reformulated this tradition in the twentieth century through *falsificationism*. According to Popper, the central task of science is not to demonstrate the truth of hypotheses but to expose them to conditions under which they might fail. If a hypothesis resists falsification, it can be provisionally accepted as "not yet falsified." However, this does not make it true. Popper's perspective implies a paradoxical condition: an empirical proposition may be neither false nor true; it may exist in a liminal state of being "not false," while still lacking the warrant to be affirmed as "true."

The framework of *Impossible Probability* departs from this Popperian approach. While falsification seeks to prove only the falsity of empirical claims, *Impossible Probability* emphasizes the demonstration of provisional truth within a defined margin of error. The distinction lies in the orientation: Popper places emphasis on the negative test (disproof), while *Impossible Probability* incorporates the logic of provisional affirmation within an explicit probabilistic framework.

26.7. Provisional Truth in *Impossible Probability*

Within the epistemological model of *Impossible Probability*, the scientific process is conceived not as the pursuit of absolute truth [unless we can create a machine like GAI able to reach that level of knowledge in the future], but as the demonstration of *provisional truth*. This provisionality arises from the acceptance of a margin of error, which itself reflects the structural limits of human knowledge. Even if an assertion proves consistent with empirical evidence for a long time, or even indefinitely, the passage of sufficient time—or the extension of the experimental domain—can reveal its falsity.

This is because ***everything that is logically possible, including error, is also—given sufficient time or an infinite horizon—inevitable***. No empirical affirmation is exempt from this rule. The statement "this is true" must always carry the qualification "within the accepted margin of error, and until proven otherwise." By introducing this probabilistic and temporal dimension, *Impossible Probability* does not negate the value of empirical truth, but rather redefines it as a dynamic, provisional construct. It asserts

that truth in science is not static but contingent, always subject to the unfolding of new possibilities that may eventually contradict what was once accepted.

26.8. The Fundamental Thesis: What Is Possible Is Inevitable

The central thesis of *Impossible Probability* can be stated as follows: *everything that is possible within a margin of logical coherence is, sooner or later, inevitable—even if its empirical probability is zero*. To illustrate this principle, let us consider the case of a biased coin. Suppose a coin has been tampered with so that, when flipped, it always lands on tails and never on heads.

Here, the empirical probability appears absolute:

- Empirical probability of heads = 0
- Empirical probability of tails = 1

From the standpoint of repeated trials, one might conclude that obtaining heads is impossible. Yet, logically, the possibility of heads exists. A coin, by its nature, carries two potential outcomes: heads or tails. The fact that repeated trials produce only tails does not erase the logical possibility of heads. Over an infinite series of trials—or given sufficient time—the inevitability of heads re-emerges. The tampering of the coin may hold across thousands, even millions, of throws, but sooner or later (perhaps by mechanical wear, structural deformation, or other unforeseen factors) the "impossible" event will occur: the coin will land on heads.

This example demonstrates the principle in its most basic form: **if something is possible, and its possibility is coherent within the logical structure of reality, then it is also inevitable**. The empirical absence of occurrence (probability zero in a given sample) does not negate the inevitability of its eventual manifestation. Thus, *Impossible Probability* radicalizes the logic of science: beyond the constraints of empirical frequency, possibility itself carries the weight of necessity.

26.9. Custom, Skepticism, and Eventual Falsity

Let us suppose that we repeatedly toss a coin and obtain tails in every single trial. From this repeated outcome, we might be tempted to formulate the empirical hypothesis that, given a sample of *N* tosses, the coin will always yield tails and that the appearance of heads is impossible. However, such a hypothesis, grounded exclusively on custom—that is, on the habitual repetition of a single result—does not guarantee truth. The habit itself generates an illusion of necessity: the more times we see tails, the more we believe that tails will continue indefinitely. Yet, over a sufficiently long duration—or within an infinite temporal horizon—this custom will eventually be falsified. At some point, the coin will land on heads, and the apparent law derived from custom will collapse. This example demonstrates the fragility of empirical generalizations based purely on repetitive experience. What appears stable in the short term is, in reality, provisional and vulnerable to eventual contradiction.

26.10. Hume's Empirical Skepticism

David Hume's doctrine of empirical skepticism begins precisely from this insight: all scientific knowledge is founded not on absolute necessity but on *custom*. According to Hume, our inferences about the future are based solely on the habitual association of events we have repeatedly observed in the past. Yet these associations have no inherent validity beyond experience itself. Thus, the fact that one event has always followed another does not mean it necessarily will in the future.

From this perspective, every scientific hypothesis based on experience is ultimately a projection of habit. No matter how extensive or "sufficient" the series of observations may be, it never guarantees certainty about what will occur tomorrow. Empirical science, therefore, cannot claim absolute predictive power. At best, it provides a probabilistic expectation, forever shadowed by the possibility of disruption. Hume's skepticism, far from undermining science, reveals its true condition: science is a practice grounded in fallible experience, perpetually exposed to revision.

26.11. Critical Rationalism as a Synthesis

Critical rationalism arises as the dialectical synthesis between two traditions: Descartes' doctrine of methodological doubt and Hume's empirical skepticism. On the one hand, Cartesian doubt requires that all scientific claims be continually subjected to rational scrutiny, ensuring that no proposition is exempt from questioning. On the other hand, Hume's skepticism demonstrates that experience itself provides no absolute certainty about the future, reducing empirical knowledge to the level of probabilistic habit.

When combined, these two insights yield the essence of critical rationalism: every empirical hypothesis that aspires to the status of scientific truth must always remain provisional, subject to rational doubt and empirical skepticism. In practice, this means that even hypotheses currently accepted as rationally valid within science—those that have passed rigorous testing—may still be false. Their acceptance is conditional upon a *margin of error*, the limit of doubt and skepticism that the scientific community is willing to tolerate at a given moment. Thus, truth in science is never absolute but always relative to the margin of error deemed acceptable.

26.12. Phenomena, Noumenon, and the Limits of Science

Critical rationalism remains, to this day, the foundation of modern science. Its enduring significance lies in its recognition of the limits of human knowledge. These limits are not primarily empirical but philosophical: they stem from the impossibility of accessing the *thing-in-itself* (*noumenon*), a concept articulated by Kant. Science can only ever grasp the *phenomena*—the appearances of things as they manifest to us within space and time.

What we know are not the essences of reality but their outward expressions, the "being-for-us" of entities as they show themselves in experience. The inner reality, the "being-in-itself," remains forever beyond the reach of empirical investigation. Science,

therefore, is restricted to constructing models of appearances, guided by the hypothetico-deductive method, in an attempt to approximate the noumenal reality without ever fully coinciding with it.

This limitation does not render science meaningless; rather, it situates science within its proper domain. It reveals that scientific knowledge is both powerful and humble: powerful in its ability to systematize and predict phenomena, yet humble in acknowledging that the ultimate reality—the noumenon—always escapes its grasp.

26.13. Synthesis Between Critical Rationalism and Positivism

From a scientific standpoint, within the framework of *Impossible Probability*, it is impossible to know *everything*. The reason is simple: we only have access to what occurs, that is, to the sample of events that reality reveals within a given space and time. Out of the totality of reality, we only grasp a fragment, and what science knows is precisely that fragment which, so to speak, reality shows of itself "outside itself." Dialectically, what reality manifests externally becomes what science assimilates and makes "its own." On the basis of this fragmentary assimilation, science formulates hypotheses—through the hypothetico-deductive method—about what reality *is in itself*. Yet, no matter how rigorous or refined, such hypotheses can never become absolutely isomorphic with reality as it is *in itself*. At best, they can strive toward approximation.

In this sense, the theory of *Impossible Probability* represents a synthesis of *critical rationalism* and *positivism*. On the one hand, it accepts the critical rationalist principle that all knowledge must remain under the jurisdiction of rational doubt. On the other hand, it adopts the positivist aspiration of constructing knowledge that is empirically grounded and progressively more faithful to reality. The innovation of *Impossible Probability* lies in its treatment of doubt. It does not endorse an unlimited or indefinite skepticism. Instead, doubt is constrained within a scientifically defined *margin of error*. This margin expresses the zone of empirical and rational uncertainty within which all hypotheses remain vulnerable to falsity.

As long as a hypothesis remains within that margin, it is provisionally valid. However, the smaller the margin of error, the closer science moves toward the moral aim of its enterprise: to generate knowledge that approximates reality itself. Scientific truth thus becomes a matter of degree: the more the hypothesis minimizes error, the greater its isomorphism with reality. By combining critical rationalism's insistence on permanent doubt with positivism's ideal of correspondence between knowledge and reality, *Impossible Probability* offers a framework in which science can progress without denying its structural limits.

26.14. Margin of Error, Critical Reason, and Critical Probability

If the rational margin of doubt—that is, empirical skepticism quantified as a margin of error—can be reduced to its minimum possible value, then science can construct a body of knowledge of increasing solidity. The objective, therefore, is not to eliminate error absolutely (which is impossible) but to reduce it as much as possible. By minimizing error, science maximizes the reliability of its hypotheses. And as reliability increases, so too does the degree of isomorphism between the empirical hypothesis and reality as it is in itself—the truly real, what actually happens.

In practice, this reduction of doubt and skepticism is achieved through the establishment of a *critical reason*. Critical reason functions as the normative boundary that science sets for the degree of error it is willing to tolerate in its acceptance of hypotheses. When formalized mathematically, this "reason" takes the form of *critical probability*. In other words, probability becomes the precise mathematical expression of rational doubt.

By defining a threshold of probability—below which a hypothesis is rejected and above which it is accepted—science articulates, in quantitative terms, the degree of skepticism it is willing to allow. The reliability of a hypothesis is thus not absolute but proportional to the size of the margin of error. Formally, reliability can be expressed as the difference between unity (perfect certainty, unattainable in practice) and critical probability (the quantified expression of the tolerated margin of doubt).

Through this mechanism, critical rationalism is given statistical expression: the margin of error becomes the operational translation of rational doubt, and probability becomes the language in which the limits of scientific certainty are formally measured.

[The positivist influence in GAI is evident, GAI means the possibility of a unified science, and if the matrix of data can be transformed into a matrix of equations, the solution of the matrix should be the equation of everything]

26.15. The Positivist Synthesis and Dialectical Materialism

Within the framework of *Impossible Probability*, we arrive at a synthesis between two major intellectual traditions: the positivist ideal of scientific isomorphism and unification through the scientific method, and the critical rationalist insistence on the permanent doubt regarding the possibility of knowing reality *in itself*—the *noumenon*.

Positivism, in its classical form, aspires to establish an identity between science and reality, such that scientific propositions would mirror, in a perfectly isomorphic way, the structure of the world. Critical rationalism, however, reminds us that such absolute identity is unattainable. The truth *in itself* can never be known directly or exhaustively; what science grasps are always appearances, *phenomena*—the outward manifestations of reality as it reveals itself in experience. The *thing-in-itself* remains inaccessible.

Impossible Probability mediates between these two positions. On the one hand, it accepts that absolute correspondence between scientific knowledge and reality is impossible. On the other, it insists that science can nonetheless approximate this correspondence as closely as possible. Through the hypothetico-deductive method, empirical hypotheses are tested within margins of error. When these hypotheses prove sufficiently consistent, they are transformed into rational hypotheses, provisionally accepted as approximations of reality. Yet even such rational hypotheses remain vulnerable: within their margins of doubt, they may, in fact, turn out to be false.

Thus, science can only ever formulate propositions that are *as isomorphic as possible* with reality, but never absolutely identical to it. The idea of a science materially identical to the world it describes is a philosophical impossibility, because human beings themselves are incapable of knowing the noumenal dimension of things. We can only know what appears to us—what presents itself externally in space and time. Everything else—the essence of things, the inner dimension of being—escapes empirical grasp and, at best, is transmitted historically in the form of interpretations, traditions, or inherited narratives.

In this way, *Impossible Probability* synthesizes positivism's aspiration toward scientific unification with critical rationalism's acknowledgment of structural limits. It grounds science in a dialectical tension: knowledge is always expanding its isomorphic reach while simultaneously recognizing that absolute identity between theory and reality is forever unattainable. This dialectic resonates with the spirit of materialism: ***reality understood as the material world exists independently of our knowledge*** of it, but our engagement with it is always mediated through appearances, hypotheses, and the historically situated processes of science itself.

[*Another point of convergence between Impossible Probability* and Marxism is the idea that every scientific revolution is potentially a social revolution. In other words, the irruption of the Artificial Intelligence Revolution will bring about potential social transformations in much the same way that the steam engine and the Industrial Revolution became the primary drivers of social revolutions in the XIX century. And another important element from the Marxist paradigm integrated in Impossible Probability is the idea that science is not neutral, **science is politics, therefore science is ideological**]

26.16. Science, Morality, and Scientific Policy

When science seeks to regulate the degree of correspondence between subject and object, it does so through the establishment of a *critical reason*. This critical reason is mathematically represented as *critical probability*, which defines the margin of error that the scientific community is willing to accept in the validation of a hypothesis.

However, the determination of this margin of error is not a purely technical or neutral matter—it is ultimately a decision of *scientific policy*.

Here lies the dialectical core of *Impossible Probability*: it not only synthesizes the epistemological insights of critical rationalism and positivism, but also incorporates the political dimension into the very structure of science. As Marx and Engels emphasized in their formulation of dialectical materialism, science is never an activity that exists in isolation from society. If the acceptance of critical reason depends on scientific policy, then science is inevitably subject to the correlation of political and social forces. Science thus becomes, in essence, not only an epistemic matter but also an ethical and moral one.

The mathematical figure of critical probability establishes a margin of error, but that margin must be consciously assumed and ratified by scientific policy. And because policy itself is always determined by ideology, every acceptance of a margin of error carries with it ideological presuppositions. In effect, each time the scientific community accepts a critical probability, it sets a threshold that reveals the tension between two kinds of morality: (a) the *political morality for-itself* of science, which reflects the ideological and institutional interests of the scientific community, and (b) the *true morality in-itself* of the universe, which corresponds to what really occurs independently of human institutions.

The divergence between these two moralities is significant. While the morality of science as an institution is shaped by political interests that are ultimately class-based and sociologically determined, the morality of the universe corresponds to the truth itself—what actually and necessarily occurs. This means that the practice of science is never value-neutral. If the object of science is to distinguish between truth and falsity, then science is, by definition, a moral undertaking. Morality, in its most basic form, consists in telling the truth. Science, therefore, is inseparably bound to morality: to produce knowledge is to make moral claims about what is and what is not true.

26.17. Empirical Hypotheses and Critical Reason

Empirical hypotheses are all propositions that must be subjected to the test of hypothesis-contrast. ***Yet not all empirical hypotheses survive this process. Only those that pass the scrutiny*** of critical reason—meaning, those that withstand testing within the accepted margin of error—become *rational hypotheses*. In other words, empirical hypotheses are numerous and varied, but rational hypotheses are the subset that meet the rigorous demands of critical probability.

This distinction underscores the fundamental role of critical reason: it acts as the filter through which empirical propositions are sifted, distinguishing those that can provisionally be treated as knowledge from those that must be discarded as unreliable. Without this filter, science would dissolve into a collection of untested statements indistinguishable from speculation. Critical reason provides the methodological safeguard that ensures empirical propositions are transformed into rationally valid scientific claims.

26.18. The Moral Validity of Science and Scientific Models

However, not all rational hypotheses possess equal moral validity. Their moral worth depends on the degree of error—or conversely, the degree of reliability—accepted in the critical probability. The lower the margin of error that scientific policy is willing to tolerate, the greater the reliability of the hypothesis, and therefore, the greater its moral validity. To accept higher error margins is, by contrast, to accept lower levels of moral commitment to truth.

Beyond this quantitative moral validity—expressed in terms of error margins and probabilities—there is also a *qualitative moral dimension*. This concerns the empirical or theoretical model within which the hypothesis is situated. The qualitative moral value of a model depends on the political and philosophical principles that underpin it.

Since every scientific policy reflects ideological commitments, the defense of a model is, in essence, a defense of specific social and class interests.

Thus, the morality of science is not abstract but concrete and socio-political. A scientific policy that serves only the narrow interests of a vertical plutocracy cannot be regarded as equally ethical as one that advances the broader interests of a horizontal democracy. The difference between these two orientations is not merely theoretical but moral: one perpetuates inequality and exclusion, while the other fosters inclusivity and collective progress. In this way, *Impossible Probability* insists that science must be judged not only by its quantitative rigor but also by the qualitative moral and political frameworks that guide its practice.

26.19. Science as a Moral Question

Science is, at its very core, a moral undertaking, and this for two fundamental reasons.

First, in a *quantitative sense*, science is moral because its primary obligation is to tell the truth. Yet absolute truth is unattainable: the *thing-in-itself* can never be known in its totality. What science can achieve is only a degree of reliability—a quantifiable margin within which hypotheses approximate reality. Thus, the moral duty of science is not to deliver absolute truth, which is impossible, but to pursue ever greater degrees of reliability, reducing error so that hypotheses more closely reflect what reality *is in itself*. The pursuit of truth in science is therefore inseparable from the moral obligation to minimize deception and error.

Second, science is also moral in a *qualitative sense*. Beyond the quantitative task of reducing error, the truth of science is always entangled with ideology, since every scientific policy is shaped by political and social interests. For this reason, the morality of science depends not only on its capacity to approximate the truth but also on the kind of social order and political interests it serves. A progressive scientific policy that defends horizontal democracy, openness, and collective participation is morally superior to a conservative policy that reinforces vertical plutocracy, hierarchy, and exclusion.

In this sense, science cannot be divorced from material history. The insights of dialectical materialism become indispensable for the critique of science: they remind us that scientific practice is always conditioned by the struggles of society, the conflicts of class, and the structures of power. To recognize science as a moral question is to understand that its truth-claims are inseparable from both its quantitative reliability and its qualitative political orientation.

[This document was written in 2012. At that time, even though I used to read everything related to AI, the concept of Superintelligence still seemed distant, something belonging to the long-term future. Now, in 2025, the situation has changed dramatically. The arrival of AGI is only a matter of time; therefore, Superintelligence is just around the corner. This is the reason why we began working on GAI in December 2017: science itself is going to change.

As soon as Superintelligence emerges, the construction of a Global AI—whether it is called GAI or by another name—will only be a matter of time. We are running against the clock: the race for Global AI has already begun. At this stage, the importance of humanity in the building of science could become null, as AI will replace humans in the production of scientific knowledge. But not only that: we are moving rapidly toward a model of automatic capitalism. In other words, every job that a machine can perform instead of human capital will be done by machines, leading to extremely high levels of unemployment.

On the other hand, even if we recognize Marx's value in the development of philosophy, his mistakes are evident. Marx believed that the working class would be the social class of the future. What is actually happening, however, is that automatic capital is replacing human capital at high speed. The dream of a working-class society is disappearing.

In the race toward AI, we are about to build the most powerful machines ever created. From our perspective, there is only one possible solution in this race: the integration of humanity within the AI framework through cyborg robotics.]

26.20. Double Scientific Critique: Quantitative and Qualitative

For these reasons, scientific critique must be *dual*. On the one hand, it must be **quantitative and rational**, assessing the degree of reliability, the margins of error, and the methodological soundness of hypotheses. On the other hand, it must be **qualitative and ideological**, evaluating the political, social, and moral frameworks that underpin scientific models and policies.

Only by integrating these two dimensions can science progress in a direction that is not merely technological but also emancipatory. Scientific advancement must be measured not only by its capacity to refine hypotheses and generate predictive power, but also by its ability to promote broader horizons of social freedom and equality.

In this dual critique lies the future of science: a system of knowledge that advances quantitatively toward greater **precision** while simultaneously advancing qualitatively toward a more just and democratic social order. Without this dual orientation, science risks degenerating either into sterile technicality divorced from human meaning, or into ideological manipulation disguised as neutral truth. With it, science fulfills its double vocation: to reveal reality as faithfully as possible, and to serve humanity in the pursuit of freedom and equality.

26.21. Origin and Struggle of Scientific Models

The origin of different scientific models lies in the succession, throughout the history of philosophy and science, of diverse philosophical frameworks and scientific policies. These successive frameworks have shaped the scientific models that exist today, which are themselves syntheses of philosophical schools and political tendencies. Scientific models, inspired by different philosophical and ideological currents, construct sets of hypotheses and theories that validate their own orientations. In doing so, they propose a particular way of understanding or studying a given field of reality, a specific science, or even a universal worldview of all phenomena. Such models may compete to become

the hegemonic paradigm for the interpretation of a phenomenon, or for a scientific field, or else strive to replace the prevailing paradigm in a particular science—or even in science as a whole.

While the qualitative and ideological dimension of scientific discourse belongs more properly to political philosophy—as the foundation of ideological politics—and although this is addressed in *Introducción a la Probabilidad Imposible, estadística de la probabilidad o probabilidad estadística*, particularly in its later sections, where a philosophical vision of science is presented from the standpoint of dialectical materialism, with special emphasis on how scientific and technological advances affect society by transforming relations of production and creating new objective social conditions, especially as automation of systems progresses—in this blog I will concentrate more on the quantitative aspects of the contradictions inherent to science, which strongly affect the occurrence of scientific revolutions.

26.22. Moral Contradictions and Paradigmatic Struggle

The principal *quantitatively moral contradiction* of science lies in the fact that any empirical hypothesis accepted through the process of hypothesis-contrast—that is, any rational hypothesis provisionally validated as true on the basis of critical reason—is only *isomorphic* with what actually occurs within the limits of an accepted margin of error. This margin of error represents, in essence, the quantified measure of doubt and skepticism that science is prepared to tolerate in relation to its hypotheses about what reality is *in itself*.

Yet this margin of doubt is not epistemically neutral. It is, in fact, a *moral margin of error*, because the decision to accept it is mediated by scientific policy. To accept a margin of error is to accept, implicitly, that what the hypothesis affirms may be false within that range of uncertainty. Since the object of science is truth, and since truth can only be accessed partially—always filtered through margins of error—the acceptance of error becomes a moral decision. Critical reason, expressed mathematically in the form of critical probability, therefore embodies the moral essence of scientific policy: it represents the threshold of truth that the scientific community is willing to accept as

morally sufficient to count as knowledge. In this way, the "truth of the universe"—what reality is in itself—becomes translated into the "moral truth" of science, mediated by human institutions and their willingness to tolerate error.

Moreover, every scientific model incorporates not only quantitative measures of reliability but also qualitative assumptions—ideological and philosophical commitments that orient scientific research toward particular objectives. These commitments, rooted in the social and political interests of the ideology sustaining scientific policy, also entail moral consequences. By aligning itself with certain social interests, each model tacitly accepts a particular margin of error as morally permissible within its framework of knowledge.

As different scientific models embody distinct ideological, philosophical, and political orientations, they inevitably come into contradiction with one another. These contradictions are not merely technical but moral and social in nature. The clash of models is thus a struggle for hegemony, in which each model seeks to transform itself into the *paradigm*: the dominant framework for understanding a given phenomenon, a particular scientific field, or even science as a whole.

This struggle is what constitutes paradigmatic conflict. It is not simply a battle of ideas, but a confrontation between different moral orders—each grounded in its own quantitative margins of error and qualitative ideological commitments. The history of science is therefore inseparable from these struggles: the transformation of paradigms is always both a scientific and a moral event, in which truth, error, politics, and ideology are dialectically entangled.

26.23. Paradigm Crisis and Scientific Revolution

The struggles between scientific models reach their highest intensity when the *dominant paradigm*—whether it concerns a specific phenomenon, an individual discipline, or science as a whole—enters into crisis. Such a situation constitutes a *paradigm crisis*. When the existing paradigm is no longer able to sustain itself, it must eventually be replaced by a new one.

The reason why a paradigm enters into crisis is, in principle, straightforward. A paradigm is built upon a scientific model that is itself sustained by a particular *scientific policy*. This policy defends a specific moral orientation, which in turn structures the theoretical framework of the paradigm: its hypotheses, its theories, and its methods of validation. But this framework always carries with it a margin of error—a moral threshold of truth accepted by the scientific community. When the political or moral foundation of the paradigm enters into contradiction with the *moral truth of the universe*—that is, with what truly occurs in reality—crisis emerges. In such cases, the error margins provisionally tolerated by the paradigm reveal themselves, in practice, as unsustainable. The invalidation of the model due to its accepted errors translates into the invalidation of the paradigm itself, whether in explaining a single phenomenon, a field of study, an entire science, or even the totality of sciences.

When a paradigm, having become dominant, enters into contradiction with reality, a paradigm crisis is inevitable. This opens the way to a new round of *paradigmatic struggle* among alternative models. Out of this struggle, one model eventually triumphs, establishing itself as the new paradigm in what we recognize as a *Scientific Revolution*.

It is important to note, however, that old paradigms do not always vanish completely. In the midst of crisis, the existing paradigm may reformulate, adapt, or transform itself in such a way that it reemerges—renewed—as the new paradigm. Whether this happens depends largely on the flexibility of the paradigm: its ability to adjust to reality and to approximate, as closely as possible, isomorphism with what actually occurs.

Moreover, the struggle for paradigmatic dominance is never determined by purely scientific factors alone. Political considerations also play a decisive role. For this reason, the establishment of a new paradigm does not necessarily mean that it is the *truest* or the most isomorphic with reality. Certain models may prevail solely because of the political or ideological interests they defend, not because of their superior scientific reliability. In such cases, paradigms are born out of ideology rather than truth, and their stability is correspondingly fragile.

If a paradigm is imposed that tolerates greater margins of error than its rivals, then its degree of isomorphism with reality will be lower. Consequently, the probability of another paradigm crisis emerging in a shorter period of time will be higher. The stability of paradigms depends, therefore, on the degree of isomorphism they achieve: the larger the margin of error, the weaker the paradigm's stability.

Nevertheless, the mere existence of a paradigm crisis does not automatically entail the occurrence of a Scientific Revolution. Whether such a revolution takes place depends on the ability of alternative models to overcome the dominant paradigm, to extend themselves across all sectors of science, and to convincingly articulate the political and philosophical assumptions that underlie them. A crisis may linger without producing a revolution if the alternatives fail to consolidate themselves.

Thus, while a paradigm crisis does not necessarily *lead* to a Scientific Revolution, such a revolution remains the most desirable outcome, for only the substitution of an inadequate paradigm with one that is more isomorphic with reality can restore stability to science. If the crisis is not resolved—either because the old paradigm persists or because it is replaced by one that is insufficiently reliable—then science risks falling into a state of *permanent crisis*.

The only true resolution of a scientific crisis is revolution: the replacement of the old paradigm with one that approaches reality more closely. Without this substitution, the scientific enterprise itself becomes unstable, perpetually trapped between inadequate models and unreliable truths.

26.24. Permanent Crisis and Permanent Scientific Revolution

A true *Scientific Revolution* occurs only when the most reliable paradigm triumphs in the paradigmatic struggle once a scientific crisis has been unleashed. However, even when such a revolution succeeds, the new paradigm that emerges is itself constructed upon theories and hypotheses that tolerate a margin of moral error. This margin may be smaller than that of the preceding paradigm, but it never disappears entirely. Error remains inevitable.

For this reason, every new paradigm, no matter how robust, carries within itself the seeds of its own eventual crisis. With the passage of time and the accumulation of anomalies, the internal contradictions of the new paradigm will inevitably be revealed, and a new crisis will arise. Out of this crisis, a subsequent Scientific Revolution must emerge, provided that another paradigm proves itself more reliable in that historical moment. Thus, the dialectic of science ensures that every paradigm, however victorious, is provisional; each revolution is not the end of history but only a temporary stabilization in the ongoing cycle of crisis and transformation.

In this sense, the progress of science can be understood as a perpetual oscillation between stability and crisis, between paradigm and revolution. The permanence of error ensures the permanence of revolution. Scientific revolutions are not isolated events but recurring necessities within the structure of knowledge itself. Science lives, advances, and regenerates through the perpetual overcoming of its own contradictions.

26.25. Science, Moral Progress, and Human Survival

As science evolves, each new crisis must be resolved by the triumph of the most reliable scientific model, giving rise to successive Scientific Revolutions. ***Yet as scientific and technological progress accelerates at an unprecedented pace, paradigms themselves collapse more rapidly, bringing about more frequent crises. This acceleration propels science into a spiral of Permanent Scientific Revolution.***

In such a context, where the rhythm of scientific and technological change becomes vertiginous***, the survival of humanity itself comes into question***. The ultimate moral duty of science is not only to seek truth but also to safeguard the continuity of the human species. Yet scientific progress alone is insufficient to secure survival. If the rapid expansion of knowledge and technology is not accompanied by a parallel *moral progress* of social forces, ***humanity risks being overwhelmed by its own creations***.

The condition for survival, therefore, lies in ensuring that the spiral of permanent scientific revolution is matched by qualitative advances in social morality—advances toward greater freedom, equality, and justice. Only if social structures evolve in tandem

with technological and scientific progress can the destabilizing effects of permanent revolution be transformed into forces for collective flourishing rather than destruction.

The destiny of humanity, then, is inseparable from the dialectic of science. The permanence of revolution in science must be matched by the permanence of revolution in morality and society. To the degree that humanity progresses morally, it will be able to harness the permanent ***revolution of science and technology as instruments of liberation and survival***. Without such moral progress, the very advances of science may turn against the species that created them.

This augmented translation is based on the post
published in https://probabilidadimposible.blogspot.com/,
On 12 October 2012,
Rubén García Pedraza
imposiblenever@gmail.com

27. Statistics—Empirical or Theoretical, Individual or Individual-Dispersion

27.1. Methods and Statistics

In the framework of *Impossible Probability*, the critique of reality—understood as the logical or political determination of events and their meaning—can be carried out through three distinct methodological pathways. This triadic structure forms the backbone of what I have termed the *statistics of probability* (or *probabilistic statistics*), a theory whose development began in the spring of 2001. The earliest of these methods emerged on the morning of September 11, 2001, only hours before the attacks in New York, and came to be known as the Method of Defect Impact. A little more than a year later, the Second Method was formulated, followed in the subsequent summer by the approach termed Effective Distribution.

The Second Method distinguishes itself from the other two by virtue of its broader range of applicability. Whereas Defect Impact and Effective Distribution are more narrowly oriented toward the measurement of defect or effectiveness, the Second Method is valid for both descriptive and inferential study of reality, whether that reality is social or natural. Its scope covers both the testing of explanatory hypotheses and the evaluation of technological hypotheses. Explanatory hypotheses aim to make sense of observed phenomena by positing correlations and causal relations. However, in the empiricist philosophy that underpins *Impossible Probability*, causal relations are not understood as necessary or universal laws but rather as patterns emerging from the contingency of chance. A single fortuitous accident may, through repetition or systemic embedding, generate regularities that appear causal but are in fact contingent. By contrast, technological hypotheses serve a different purpose: their goal is to establish, through

scientific validation, the degree to which a given technology is capable of controlling, directing, or manipulating aspects of an otherwise variable and uncertain reality.

In this sense, Defect Impact and Effective Distribution are more specialized. They concentrate on measuring the degree of defectiveness or effectiveness, whether this is the result of an isolated accident or an inherent property of a contingent system. The Second Method, however, seeks to generalize beyond measurement of defect to a more comprehensive synthesis of statistical reasoning and probabilistic analysis.

The nomenclature of the Second Method reflects this ambition. Although it arose after Defect Impact, the name “second” signals its relationship to traditional statistics, which is referred to here as the First Method. This First Method remains the dominant paradigm in contemporary statistical practice. It is characterized by a rigid division between (a) statistical study, which focuses on measures of central tendency (mean, mode, median) and measures of dispersion (mean deviation, variance, standard deviation), and (b) probability theory, which studies the likelihood of events. In this conventional framework, the probability of an event is defined operationally as the number of occurrences of a given type divided by the total number of all observed events across categories.

In contrast, the Second Method of *Impossible Probability* rejects this hermetic separation and proposes instead a synthesis of statistics and probability. To achieve such integration, it introduces novel conceptual tools: empirical probability, theoretical probability, and critical probability. The latter, in particular, is of great importance: it represents the mathematical formalization of critical reason, the evaluative standard chosen by scientific policy according to the margin of error deemed acceptable. On this foundation emerges a new, unified framework: the statistics of probability, also referred to as probabilistic statistics, which constitutes the methodological identity of the Second Method.

Up to this point, the models of inference developed within *Impossible Probability* have been primarily individual in focus. They operate through evaluative categories such as Validity and Significance, applied to tests of Equality, Positive Bias, or Negative Bias. In *normal models*, the measure of evaluation is the Level of Bias, defined as the difference

between empirical and theoretical probability. In *omega models*, by contrast, the relevant comparison is between empirical probability and ideal probability. Subsequent sections will expand upon these approaches, especially the development of sample-level critique, where the emphasis shifts from individual probabilities to the overall tendencies of the sample.

Despite these differences of scale, the general procedure in *Impossible Probability* remains consistent. The process begins by determining empirical and ideal values, which are then compared within an accepted margin of error. This margin is mathematically defined by the concept of critical probability, which quantifies the degree of doubt or tolerance for error adopted by scientific policy. On the basis of this comparison, a statistical decision is reached concerning whether the observed trend is sufficient to treat a given empirical hypothesis as rational, thereby granting it provisional acceptance within the broader framework of scientific theory.

It follows that hypothesis testing, in this system, is not merely a technical procedure but an intellectual exercise in contrasting ideas. At its heart lies the question of whether the observed relationship between empirical and theoretical values provides adequate grounds for provisional rational acceptance. Every hypothesis is, in this light, a conceptual construction—an idea formed by the combination of variables—that must be tested against reality to determine whether it can move from the subjective realm of conjecture to the partially objective realm of rational science.

Within this framework, the role of statistics is indispensable. The act of testing hypotheses is, fundamentally, the act of testing statistics, since it is through statistical quantities that empirical and theoretical comparisons are made possible. In the theory of *Impossible Probability*, a statistic is defined as any numerical value within a statistical framework that expresses a determinate tendency. Such tendencies, when properly analyzed, provide the critical foundation for transforming isolated observations into rational hypotheses and, ultimately, into provisional scientific knowledge.

27.2 Traditional Statistics

Within **traditional statistics**, designated here as the **First Method**, descriptive statistics are normally classified into only two categories: **statistics of central tendency** and **statistics of dispersion**. This dual classification has long structured the field of classical statistical analysis.

Statistics of central tendency are numerical values that describe the points in a distribution where the maximum concentration of elements is found, or alternatively, positions that represent the central or intermediate plane of the distribution. The purpose of these measures is to provide a single, representative figure around which the observed data appear to cluster.

Traditional statistics identifies three canonical measures of central tendency: the **mode**, the **median**, and the **arithmetic mean**. The **mode** is defined as the value with the highest frequency of occurrence. For instance, if one conducts a large number of coin tosses and, by chance, obtains more heads than tails, then the mode of the distribution will be “heads.” Conversely, if tails appear more often, the mode will be “tails.” The **median**, by contrast, is the fiftieth percentile of a distribution. It is determined by ordering the sample and examining the cumulative frequencies. The value at which the cumulative distribution reaches fifty percent is identified as the median. For example, if we compile a dataset measuring the intensity of solar storms over a given period, and for each storm we add the intensity of all preceding storms (measured perhaps in energy output, solar wind speed, or another positive variable), the resulting cumulative frequency allows us to calculate percentages. The value that contains within itself fifty percent of the cumulative frequency is, by definition, the median. The **arithmetic mean** (or simply, the “mean”) is perhaps the most widely used measure of central tendency. It is defined as the sum of all observed values divided by the total number of observations in the sample, thus providing a simple numerical average.

In contrast, **statistics of dispersion** measure the degree to which the elements of the sample are spread out around these central values. They indicate whether the data points are tightly clustered or widely dispersed. The most common measures of dispersion in the First Method are the **mean deviation**, the **variance**, and the **standard deviation**. All three are grounded in the concept of a **differential score**, defined as the difference between an individual observation (the direct score) and the arithmetic mean. The **mean deviation** is then calculated as the average of the absolute values of these differential scores. The **variance** takes these differential scores, squares them to eliminate negative signs, and then averages the squared values. Finally, the **standard deviation** is obtained by taking the square root of the variance, thereby restoring the original units of measurement. Together, these measures allow traditional statistics to describe not only where the bulk of observations lie, but also how far, on average, individual values deviate from that central position.

This dual classification—central tendency versus dispersion—has long dominated statistical analysis and remains the basis for the interpretation of empirical data in the First Method. Yet, as will be shown, the theory of *Impossible Probability* (the Second Method) critiques this binary framework, arguing that even measures traditionally understood as "central" are, in fact, measures of dispersion when examined through a more critical and dialectical lens.

27.3. Statistics in *Impossible Probability*

While the First Method reduces the field of statistics to a strict division between **central tendency** and **dispersion**, the **Second Method** of *Impossible Probability* introduces a more complex and nuanced classification. This complexity arises because the Second Method does not merely treat statistics and probability as separate domains but rather synthesizes them into a unified field—the **statistics of probability** or **probabilistic statistics**. In this perspective, statistics are not only tools for describing data but also instruments for understanding the **distribution of chance across space and time**, what the theory calls the **history of contingency**.

Accordingly, *Impossible Probability* distinguishes between several categories of statistics:

1. **Individual statistics**, which may be either empirical or theoretical.
2. **Individual-dispersion statistics**, which may likewise be empirical or theoretical.
3. **Sample-dispersion statistics**, again empirical or theoretical.

An additional case is the statistic known as the **inverse of N (1/N)**. While this measure might at first appear to belong to central tendency, in the Second Method it is revealed as a **multifunctional statistic**, operating simultaneously as a measure of centrality and as a measure of dispersion.

In the present section, attention is directed to **individual statistics** and **individual-dispersion statistics**, both empirical and theoretical. This will lead to the introduction of key intermediate measures such as the **intermediate probability** and the **intermediate deviation**. The following section will then focus on **sample-level statistics of dispersion**, continuing the systematic expansion of the statistical apparatus of *Impossible Probability*.

It is important to note why *Impossible Probability* downplays the role of central tendency as conventionally understood. The reason is that, from its standpoint, **all tendencies are tendencies of dispersion**. Even those statistics that in the First Method are classified as central are, upon closer inspection, measures of how values are dispersed relative to one another. For example, what traditional statistics identifies as the **mode**—the most frequent outcome in a distribution—is reinterpreted in the Second Method as the **maximum**: the subject or option with the greatest **positive individual dispersion** in the sample, corresponding to the tendency toward the **Maximum Theoretical Positive Bias**. Similarly, the inverse of N (1/N), far from being a simple measure of centrality, functions as a measure of **theoretical dispersion**: as N increases, the probability of dispersion decreases; as N decreases, dispersion

increases. In universes with limited options, theoretical dispersion is inversely proportional not to N itself but to the sum of direct scores or frequencies.

Through these reconceptualizations, the Second Method of *Impossible Probability* breaks down the rigid distinction between centrality and dispersion, replacing it with a **dialectical framework** in which every measure reflects, in some way, the inherent dispersion of chance.

27.3.1. Theoretical Individual Statistics

By *individual statistics* we mean those **positive numerical values** that possess the capacity to quantify a specific **tendency**. A tendency, in this context, is simply a form of **behavior**; behavior itself may be described as a tendency toward a certain outcome. From a theoretical perspective, the ideal would be for every subject or option to approximate the **ideal behavior** defined by the objectives of **scientific policy**.

Here it is important to distinguish between **individual behavior** and **sample behavior**. While the behavior of a sample is ultimately determined by the aggregate of its elements, the logical basis of this aggregate lies in the statistics that describe individual behavior. Each element in a sample displays a behavior that may be accidental or contingent. The task of science is to determine whether these accidents can be transformed into **regular and reliable patterns**. In other words, the challenge is to see whether chance contingencies can crystallize into stable, predictable tendencies. This verification process is guided by theoretical statistics established *a priori* and by the ideals set forth by scientific policy.

Thus, theoretical individual statistics are dependent upon the framework and objectives of scientific policy at the level of individual behavior. Once these statistics are established, they serve as the basis for the construction of **models of theoretical individual dispersion**, which in turn allow for a rational critique of individual outcomes and the determination of **critical probability**. Critical probability is the mathematical representation of the **critical reason** through which scientific policy decides whether a hypothesis is to be provisionally accepted.

27.3.1.1. Theoretical Individual Statistics

Theoretical individual statistics represent models of idealized behavior according to pre-established principles defined by the orientation and goals of scientific policy. Among them, one of the most central is the **inverse of N (1/N)**, which possesses a remarkable **multifunctionality**. This measure operates across virtually all areas of *Impossible Probability*, making it one of the most important theoretical statistics within the framework.

27.3.1.1.1. Theoretical Probability: The Inverse of N (1/N)

The inverse of N (1/N) functions as the **theoretical probability of occurrence by chance under conditions of equal opportunity**. At the individual level, it provides the mathematical expression of fairness, ensuring that each subject or option has the same probability of occurrence. Accordingly, in studies where the objective is to guarantee equality of opportunity across all events, the ideal distribution is one in which observed values tend toward 1/N.

$$\text{Theoretical Probability} = \frac{1}{N} \quad \rightarrow \quad \text{guarantees equality of opportunity by chance.}$$

27.3.1.1.2. The Maximum Possible Empirical Probability

In any probabilistic model, the maximum possible empirical probability can only be equal to **one**. This follows directly from probability theory, which restricts probability values to the closed interval between zero and one. Thus, the highest probability that can ever be observed or assigned is unity.

This ideal is particularly relevant in **“normal” models of growth** where, out of all N elements, only one subject or option is regarded as ideal. In such cases, the theoretical goal is that this ideal option tends toward an **empirical probability of one**.

$$\text{Maximum Possible Empirical Probability} = 1 \quad \rightarrow \quad \text{Ideal in normal models with positive bias.}$$

[What I refer to here as the *Maximum Possible Empirical Probability* may, in other contexts or texts, appear under the name *Maximum Possible Theoretical Probability* or simply *Maximum Theoretical Probability*. Due to the circumstances in which I have developed my work, it is difficult to explain why this variation in terminology has occurred. In any case, the *Maximum Possible Empirical Probability* is, in reality, a theoretical case scenario. Even though our ultimate goal is to reach the *Maximum Possible Probability*—that is, one (1)—this is not always achievable.

For example, consider a survey about ecological behaviors. If the question is “Do you recycle?” and the possible answers are “yes,” “no,” and “no answer,” the ideal outcome would be for “yes” to reach the *Maximum Possible Empirical Probability* of one (1). The truth, however, is that this ideal is not realized in practice.]

27.3.1.1.3. The Minimum Possible Empirical Probability

Conversely, in models where certain subjects or options are designated as non-ideal—whether in normal or omega frameworks—the goal is for their empirical probability to approach **zero**. In *Impossible Probability*, it is regarded as irrational to attribute a **negative probability** to a positive event. A probability less than zero is logically contradictory, since it would imply that a real event is “less than impossible.” For this reason, the lowest theoretical value assignable to a positive phenomenon is zero.

$$\text{Minimum Possible Empirical Probability} = 0 \quad \rightarrow \quad \text{Ideal in models with negative bias.}$$

[The *Minimum Possible Empirical Probability*, zero (0), may in other writings appear as the *Minimum Possible Theoretical Probability*, also zero (0). I have developed *Impossible Probability* under the most extreme conditions, and it is therefore difficult to explain why the terminology may vary at times. In any case, the *Minimum Possible Empirical Probability*, zero (0), is in reality a theoretical case scenario.

For example, if we conduct a survey where the ideal outcome is that the empirical probability of "non-recycling" equals zero (0), the truth is that this ideal is never fully realized in practice.]

27.3.1.1.4. The Ideal Probability (1/Ω)

Omega models introduce an additional level of complexity. Given a population of N subjects or options, suppose there exists a **subset of ideal subjects** smaller than N but greater than one. This subset, denoted by the symbol **Ω (omega)**, may consist of any number of ideals between two and N-1. For such a configuration, the **ideal probability** is defined as the reciprocal of the number of elements in Ω.

$$\text{Ideal Probability} = \frac{1}{\Omega}$$

In this way, if Ω contains k ideal subjects within the total population, the probability ideal is distributed evenly across those k elements. The principle behind 1/Ω thus formalizes a policy of **equitable occurrence among multiple ideals**.

In summary, theoretical individual statistics depend upon the orientation and goals of scientific policy. If the policy objective is to guarantee equality of opportunity in a normal model, the ideal statistic is the **inverse of N (1/N)**. If the goal is to maximize the probability of a specific ideal subject, the ideal becomes the **maximum possible**

empirical probability (1). For non-ideal subjects, the ideal is the **minimum possible empirical probability (0)**. And in omega models, the objective of equity among multiple ideals is expressed through the **ideal probability (1/Ω)**.

Through these constructs, *Impossible Probability* develops a flexible and dialectical approach to theoretical statistics—one that integrates notions of fairness, growth, exclusion, and equity into a coherent probabilistic framework.

27.3.1.2. Theoretical Individual-Dispersion Statistics

Once the **theoretical individual statistics** have been established, it becomes possible to define the corresponding **ideals of individual empirical dispersion**. These ideals provide the benchmark against which actual behaviors may be measured and evaluated.

In **traditional statistics (the First Method)**, the entire theory of dispersion is constructed on the basis of the **differential score**. This is defined as the difference between an individual's direct score (its observed value) and the arithmetic mean of the distribution. From these individual deviations, one subsequently derives **sample-level dispersion statistics** such as the mean deviation, variance, or standard deviation.

By contrast, in the **Second Method of *Impossible Probability***, where analysis is conducted using **empirical probabilities**, the differential score is redefined. Instead of the observed value minus the mean, it becomes the difference between the **empirical probability** of an event and its **theoretical probability**. This difference is called the **Level of Bias**. Consequently, any theoretical idealization of what the dispersion of a given subject or option *ought* to be—according to the ethical or political aims of scientific policy—must be constructed on the basis of these theoretical statistics.

From this foundation, three principal measures of **theoretical individual dispersion** are defined:

27.3.1.2.1. Maximum Possible Theoretical Bias

If the **maximum possible empirical probability** is equal to one, then the **maximum possible theoretical bias** can only be defined as the difference between unity and the theoretical probability.

$$\text{Maximum Possible Theoretical Bias} = 1 - \frac{1}{N}$$

This measure represents the upper bound of deviation a subject may attain in a positive direction relative to its theoretical expectation.

27.3.1.2.2. Maximum Possible Negative Bias

By logical symmetry, if the **minimum possible empirical probability** is zero—and if negative probabilities are deemed irrational in *Impossible Probability* (since it would be contradictory to assign a negative likelihood to a positive event)—then the **maximum possible negative bias** is defined as zero minus the theoretical probability.

$$\text{Maximum Possible Negative Bias} = 0 - \frac{1}{N}$$

This measure establishes the lower bound of deviation, representing the maximum possible negative departure from theoretical expectation.

27.3.1.2.3. Ideal Bias

In **omega models**, where the set of ideals consists of a proper subset of N (larger than one but smaller than N), the **ideal probability** is defined as 1/Ω. Consequently, the **ideal bias** must be the difference between this ideal probability and the theoretical baseline probability (1/N).

$$\text{Ideal Bias} = \frac{1}{\Omega} - \frac{1}{N}$$

This statistic measures the extent to which the presence of multiple coexisting ideals modifies the expected dispersion relative to the principle of equal opportunity.

27.3.2. Empirical Individual Statistics and Empirical Individual-Dispersion Statistics

The reason for introducing the **theoretical individual statistics** and their dispersion measures before turning to the empirical domain is methodological. Having already defined these theoretical constructs, it becomes easier to grasp what is meant by their **empirical counterparts**. The theoretical statistics serve as the normative or ideal benchmarks, while the empirical statistics provide the actual observed values against which hypotheses can be tested.

Thus, while the theoretical and theoretical-dispersion statistics are established according to the **orientation and goals of scientific policy**, the **empirical individual statistics** represent the **observed models of individual behavior within a sample**. These empirical values form the raw material for critique and for the construction of subsequent hypothesis-testing models. Once collected and analyzed, they allow for the formalization of **individual hypothesis contrasts**. From there, one can also construct models of **sample-level hypothesis testing**, which will be addressed later in the central sections of *Impossible Probability: The Statistics of Probability, or Probabilistic Statistics*.

The central contribution of this stage—both in the blog and in the corresponding sections of *Impossible Probability* (notably Section 11 of the *Introduction*)—is to **systematize the exposition of statistics**. This systematic framework facilitates the introduction of **empirical individual statistics**, which will prove to be of fundamental importance, particularly when deriving certain **empirical dispersion statistics**, whether at the level of the individual or at the level of the sample.

27.3.2.1. Empirical Individual Statistics

Empirical individual statistics are those numerical measures that arise directly from **observed behavior** in a given period and space of observation. They capture how a particular subject or option behaves within a specific history and thereby delimit its **empirical behavioral model**. In formal terms, the empirical probability of a subject or option is defined as the ratio of its **direct value or individual frequency** to the **sum of all direct values or frequencies** in the sample.

$$p(x_i) = \frac{x_i}{\Sigma x_i}$$

This fundamental measure, p(xi), provides the statistical foundation for modeling individual empirical tendencies.

27.3.2.1.1. Empirical Probability, p(xi)

The empirical probability of a subject or option, p(xi), is the most basic empirical statistic. It defines the observed probability of that subject or option in relation to the entire sample space. By quantifying its relative frequency, it sets the **pattern of behavior** that characterizes the subject within its given observational context. This

measure recurs throughout the theory of *Impossible Probability*, serving as the empirical analogue to the theoretical probability (1/N).

27.3.2.1.2. Maximum Empirical Probability, p(xi+)

The **maximum empirical probability**, denoted p(xi+), corresponds to the subject or option within a given sample that exhibits the **highest probability of occurrence**. In practice, this is the "dominant" element of the distribution.

$$p(x_i^+) \approx 1 \quad \Rightarrow \quad \text{Closest to the Maximum Possible Empirical Probability.}$$

In general, the subject with maximum empirical probability will also exhibit a **positive bias level** (p(xi+)−1/N approaching the **maximum possible theoretical bias** (1−1/N). Thus, this statistic identifies the element of the sample whose observed frequency most closely approximates the ideal of empirical dominance.

[The difference between the *Maximum Possible Empirical Probability* (1) and the *Maximum Empirical Probability* p(xi+) lies in the fact that the subject or option with the highest score or frequency in a sample will represent the empirical maximum value, but this value will not necessarily equal one. The gap between the maximum in the sample (the *Maximum Empirical Probability*) and the *Maximum Possible Empirical Probability* (1) is precisely the difference that separates the empirical maximum from the theoretical upper limit of any probability.

As noted before, the *Maximum Possible Empirical Probability*—one (1)—is, in reality, a theoretical value.]

27.3.2.1.3. Minimum Empirical Probability, p(xi−)

Conversely, the **minimum empirical probability**, p(xi−), denotes the subject or option with the **lowest probability of occurrence** within the sample.

$$p(x_i^-) \approx 0 \quad \Rightarrow \quad \text{Closest to the Minimum Possible Empirical Probability.}$$

This subject is typically associated with a **negative bias level**, approximating the **maximum possible negative theoretical bias**:

$$(p(x_i^-) - 1/N) \approx (0 - 1/N).$$

Thus, p(xi−) identifies the “least frequent” element of the distribution, offering insight into the tail behavior of the sample.

[While the *Minimum Empirical Probability* p(xi−) refers to the subject or option in the sample with the lowest empirical probability, this does not necessarily mean that it equals zero (0), the *Minimum Possible Empirical Probability*. If the ideal for that subject or option is to be zero, then the difference between the *Minimum Empirical Probability* and zero—therefore, the *Minimum Empirical Probability* itself—represents the distance between its empirical value and its ideal target.

Once again, it must be emphasized that the *Minimum Possible Empirical Probability*, zero (0), is in fact a theoretical value: the lower limit within the probability system.]

27.3.2.1.4. Empirical Probability Closest to the Inverse of N, p(xi≈)

The **empirical probability closest to the inverse of N**, p(xi≈), designates the subject or option whose empirical value or frequency is most similar to the **theoretical probability of equal opportunity** (1/N).

$$p(x_i \approx) \approx \frac{1}{N}, \quad (p(x_i \approx) - 1/N) \approx 0$$

This statistic is particularly significant in studies where the normative ideal is **equality of opportunity**. In such contexts, the "most normal" subject is the one whose behavior most closely reflects theoretical fairness, i.e., the one with the smallest deviation from the ideal distribution 1/N.

27.3.2.1.5. Intermediate Probability, p(xi+/−)

The **intermediate probability**, denoted p(xi+/−), is defined as the value obtained by dividing by two the sum of the maximum and minimum empirical probabilities:

$$p(x_i^{+/-}) = \frac{p(x_i^{+}) + p(x_i^{-})}{2}$$

This measure represents the **equidistant probability** between the extreme values of the sample. Its interpretation, however, varies depending on the type of model:

- In models of equality of opportunity, the intermediate probability will tend toward the theoretical baseline, 1/N.
- In normal models with positive bias, the intermediate will tend toward 0.5.
- In omega models, the intermediate probability will fall **below 0.5**, with its exact value depending on the size of the ideal subset Ω. For example, if all ideals in Ω share the same probability (1/Ω), the intermediate probability will tend toward (1/2)·(1/Ω).

Thus, while the value of p(xi+/−) is context-dependent, its **definition as the midpoint between extremes** remains consistent across models.

27.3.2.2. Empirical Individual-Dispersion Statistics

Moving beyond simple empirical probabilities, *Impossible Probability* also defines statistics of **individual dispersion**. These measures are critical because they quantify the degree to which an individual subject's probability deviates from its theoretical expectation.

The most fundamental of these is the **Level of Bias (Nivel de Sesgo)**, which expresses the difference between the empirical and theoretical probabilities:

$$\text{Level of Bias} = p(x_i) - \frac{1}{N}$$

This statistic captures, in a single value, whether a subject occurs **more frequently** (positive bias) or **less frequently** (negative bias) than expected under the principle of equal opportunity.

In addition to the Level of Bias, two further statistics are defined at the individual level but also have implications for the sample as a whole:

1. The **Maximum Possible Empirical Bias**, which sets the upper bound for observed deviations within a given sample.
2. The **Intermediate Dispersion**, defined as half the difference between the maximum and minimum empirical probabilities.

These additional measures will be explained in detail when examining **sample-dispersion statistics**, since their full significance becomes apparent only in relation to the aggregate properties of the distribution. For now, it is sufficient to note that the **mean deviation of empirical probabilities can never exceed the intermediate dispersion**, a constraint that will play an important role in later analysis.

27.3.2.2.2.2. Maximum Possible Empirical Bias

The **Maximum Possible Empirical Bias** is defined as an **individual empirical-dispersion statistic**, and it occupies an important place within the framework of *Impossible Probability: The Statistics of Probability, or Probabilistic Statistics*. Its relevance is not merely theoretical, but also practical, particularly in relation to models of hypothesis testing based on ratios and differential contrasts. The notion is introduced explicitly in *Impossible Probability* and appears in greater detail in earlier expositions, such as the entry of February 26, 2012, in the foundational blog. Although later developments emphasized more strongly the role of the **Maximum Possible Theoretical Bias**, especially in the calculation of **critical probability** within the frameworks of Validity of Equality or Significance of Equality (both under positive bias), the empirical version remains a necessary complement.

From the standpoint of **scientific policy**, the establishment of a rational critique of dispersion must ultimately rest on theoretical ideals. In this sense, the critical reason that guides the acceptance of error margins is most logically anchored in the **Maximum Possible Theoretical Bias** or its negative counterpart, depending on the situation.

These theoretical extremes provide the rational and ideological foundation for constructing the **critical reason**, mathematically expressed as critical probability. Nevertheless, it remains conceptually important to recognize that there exist circumstances where the **Maximum Possible Empirical Bias** becomes analytically valuable.

Formally, the Maximum Possible Empirical Bias is defined as **one half of the Total Bias of the sample**. The Total Bias, in turn, is the **sum of the absolute values of all Levels of Bias** for each subject or option. Thus:

$$\text{Maximum Possible Empirical Bias} = \frac{\Sigma|p(x_i) - 1/N|}{2}$$

This formulation arises from a simple but powerful principle: given any distribution of bias within a sample, it is statistically impossible for any single subject to exhibit a Level of Bias greater than half the Total Bias of the entire sample. By definition, the Total Bias represents the aggregate imbalance between observed empirical probabilities and their theoretical expectations. Dividing this value by two yields the maximum possible deviation—positive or negative—that any one element could sustain.

The logic underpinning this definition is rooted in a fundamental law of probability and dispersion: the **sum of all positive biases must equal the sum of all negative biases**, once signs are taken into account. Expressed differently, the universe of chance imposes a natural balancing principle—every excess in one direction must be offset by a deficit in the other. This means that when Levels of Bias are aggregated with their signs, the sum is identically zero. For this reason, any meaningful measurement of dispersion must operate with the **absolute values** of the Levels of Bias. Only by considering absolute deviations can we capture the true magnitude of dispersion, whether positive or negative.

Thus, the Total Bias provides the comprehensive measure of absolute deviations, while dividing it by two yields the Maximum Possible Empirical Bias. This statistic, therefore, sets the **upper bound of deviation** achievable by any single element in the sample. It cannot be exceeded, under any statistical configuration, since the collective deviations constrain the extremes. In this way, the Maximum Possible Empirical Bias is not only a theoretical construct but also a **structural limit** imposed by the very logic of statistical distributions.

In summary, while the **Maximum Possible Theoretical Bias** retains primacy for establishing rational critiques and for calculating the acceptance thresholds of scientific policy, the **Maximum Possible Empirical Bias** provides an indispensable complementary measure. It allows researchers to anchor their analyses in the actual configuration of observed data, ensuring that any interpretation of individual dispersion remains consistent with the inherent constraints of the distribution as a whole.

27.3.2.2.3. Intermediate Dispersion

The **Intermediate Dispersion** is defined as half the difference between the maximum and minimum empirical probabilities within a given sample:

$$\text{Intermediate Dispersion} = \frac{p(x_i^+) - p(x_i^-)}{2}$$

This measure differs fundamentally from the **Intermediate Probability**. Whereas the Intermediate Probability is computed as the midpoint between the maximum and minimum probabilities—i.e., half their sum—the Intermediate Dispersion measures the **distance** from this midpoint to each extreme, i.e., half their difference. In other words:

- The Intermediate Probability identifies the **equidistant point** between the maximum and the minimum values.
- The Intermediate Dispersion quantifies the **half-range**, or the symmetric distance separating that midpoint from the extremes.

The value of Intermediate Dispersion allows us to define an important boundary: the **Maximum Possible Intermediate Dispersion**. This occurs only under one condition: when the maximum empirical probability, p(xi+), reaches the **Maximum Possible Empirical Probability** (i.e., equals 1), and simultaneously, the minimum empirical probability, p(xi−), reaches the **Minimum Possible Empirical Probability** (i.e., equals 0). Under such circumstances:

$$\text{Maximum Theoretical Intermediate Dispersion} = \frac{(1-0)}{2} = \frac{1}{2} = 0.5$$

Thus, the theoretical upper limit of Intermediate Dispersion is 0.5, a value that is only attainable in the extreme case where one element fully dominates the distribution (probability 1), while the other ones vanishes entirely (probability 0).

The essential property of Intermediate Dispersion is therefore its **boundedness**: it can never exceed 0.5. In practice, this ensures that dispersion between extremes remains a contained measure, providing a natural ceiling for statistical evaluation. Moreover, Intermediate Dispersion is applicable across **any universe of observation and any sample size**.

By contrast, the Intermediate Probability loses interpretive value in binary universes (samples with only two options). In such cases, the Intermediate Probability is always and necessarily 0.5, regardless of the data configuration. Intermediate Dispersion, however, continues to yield meaningful information about the spread of the

distribution, even in two-option universes. Its independence from sample size or universe type makes it a more versatile and reliable indicator.

Because of this versatility, Intermediate Dispersion can also be treated as a **sample-dispersion statistic**. By simply dividing by two the difference between maximum and minimum probabilities, researchers obtain a quick and practical approximation of the overall behavior of dispersion in the sample. This provides a rapid tool for assessing the **structural variability** of empirical data, without requiring more elaborate calculations.

27.3.3. Toward Sample-Dispersion Statistics

Once the **individual statistics** have been clearly defined, they provide the foundation upon which the broader edifice of probabilistic statistics can be constructed. It is on the basis of individual maxima, minima, intermediate values, and associated bias levels that we proceed to model the behavior of entire samples.

In sample-level analysis, traditional measures such as **Mean Deviation, Variance, and Standard Deviation** reappear, but they are reconceptualized within the framework of *Impossible Probability*. Additionally, upper bounds are defined for these measures—such as the **Maximum Possible Mean Deviation**, the **Maximum Possible Variance**, and the **Maximum Possible Standard Deviation**. Alongside these, the Intermediate Dispersion re-emerges as a quick proxy for assessing dispersion at the sample level, providing an immediate sense of deviation around the midpoint between extremes.

Furthermore, *Impossible Probability* introduces the concept of the **Maximum Possible Empirical Mean Deviation**, also called the **Mean Deviation of Maximum and Minimum**. This measure is obtained by averaging the absolute values of the bias levels corresponding to the maximum and minimum empirical probabilities:

$$\text{Mean Deviation of Maximum and Minimum} = \frac{(p(x_i^+) - 1/N) + (1/N - p(x_i^-))}{2}$$

Although this measure does not capture the mean deviation of the entire sample (since it only considers two elements), it nevertheless provides a useful empirical benchmark. It represents the **upper limit** of what the sample's mean deviation could be, as the mean deviation can never exceed the average of the absolute biases of the maximum and minimum.

In this sense, the Mean Deviation of Maximum and Minimum operates as a **practical ceiling** for empirical mean deviation, offering a way to gauge the dispersion structure of the sample in a simplified yet rigorous manner.

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On 21 October 2012,
Rubén García Pedraza
imposiblenever@gmail.com

28. Maximum Biases, Intermediate Dispersion, and Mean Deviation of Maximum and Minimum

28.1. Maximum Biases, Intermediate Dispersion, and Mean Deviation of Maximum and Minimum

Throughout this blog, particular emphasis has been placed on the concepts of the *Maximum Theoretical Bias Possible* and the *Maximum Negative Bias Possible*. These constructs have been prioritized over other types of maximum-bias measures, such as the *Maximum Empirical Bias Possible* or *Intermediate Dispersion*, which are discussed in greater detail in the book *Introduction to Impossible Probability: Statistics of Probability or Probabilistic Statistics*.

The reason for this prioritization is didactic. Since the main pedagogical objective of this blog has been to provide an initiation into the framework of *Impossible Probability*, it has been necessary to start by clarifying in depth the nature and properties of the Maximum Theoretical Bias and the Maximum Negative Bias. These two measures are the foundation for understanding the operation of *critical reason*, which is mathematically expressed as *critical probability*. By mastering these constructs, the reader acquires the conceptual tools required to engage with the rational critique of empirical phenomena, especially in the context of *individual rational critique models*. Up to this point, the blog has intentionally presented only a limited set of models from the much wider repertoire of contrastive frameworks developed in the larger theoretical work.

28.2. Diversification of Models in Impossible Probability

As the theory of *Impossible Probability* develops, the repertoire of available models inevitably diversifies. New mathematical formulations and statistical expressions emerge, each addressing specific problems or offering alternative perspectives. Yet despite this diversification, all of these models remain intimately connected: they are not isolated inventions but rather logical extensions of the same foundational principles.

This diversification reflects the dialectical structure of the theory itself. By confronting new empirical or theoretical challenges, *Impossible Probability* expands its analytical capacity while maintaining coherence through the unifying framework of bias (or *sesgo*). Thus, every new measure—whether theoretical or empirical, individual or sample-based—ultimately derives from the same methodological foundation: the systematic comparison between empirical probability, theoretical probability, and the acceptable margin of error as defined by scientific policy.

28.3. Bias Level in Relation to the Traditional Differential Score

In traditional statistics (what this work refers to as the *First Method*), dispersion is defined in terms of the *differential score*—that is, the difference between an individual's direct score and the arithmetic mean of all scores in the sample. This provides a way of measuring how far an individual observation deviates from the central tendency of the dataset.

In *Impossible Probability*, however, this concept is reformulated. The differential score is replaced by the concept of the *Bias Level* (*Nivel de Sesgo*) for each subject or option. The Bias Level is calculated as the difference between empirical probability and theoretical probability. In other words, it measures how much the actual empirical behavior of a given subject or option deviates from what its behavior *should theoretically be* under conditions of perfect fairness, chance, or equality of opportunity.

If, in accordance with the principle of equal opportunities, all outcomes were governed purely by chance, then each subject or option would follow the theoretical distribution given by the *inverse of N* (1/N). Thus, the Bias Level quantifies the distance between the empirical frequency of occurrence and this theoretical baseline. It therefore captures the extent to which reality diverges from the idealized model of randomness.

This shift—from the traditional concept of differential score to the probabilistic notion of Bias Level—marks one of the most significant differences between *Impossible Probability* and conventional statistics. Where the First Method describes deviations from an empirical mean, the Second Method redefines deviation in terms of the gap between empirical reality and theoretical fairness. This not only preserves the descriptive function of dispersion but also introduces a normative dimension, linking statistics directly to questions of equality, fairness, and scientific rationality.

28.4. Positive Bias Models and Maximum Empirical Probability

The *Bias Level* measures the difference between the actual empirical behavior of a subject or option and the theoretical behavior it should exhibit under conditions of equal opportunity. Depending on the focus and purpose of the study, the “ideal” form of bias will vary.

When the research objective is to privilege one particular subject or option above all others within a set N, this constitutes what is known as a *positive bias model*. In such a model, out of the entire N, only one subject or option is considered “ideal.” Consequently, the expectation is that this ideal subject or option will converge toward the maximum—that is, the *maximum empirical probability*, denoted p(xi+). Ideally, this maximum should approximate as closely as possible the *Maximum Empirical Probability Possible*, equal to 1.

This structure necessarily implies that if, in a set of size N, only one element is ideal, then the remaining N−1 elements must be non-ideal. For these non-ideal subjects or options, the empirical probability must tend toward the minimum—the *minimum*

empirical probability, denoted p(xi−)—which should approximate the *Minimum Empirical Probability Possible*, equal to 0.

Thus, in a model where a single ideal is contrasted with N−1 non-ideals, the theoretical expectation is that the Bias Level of the ideal, as the maximum, will converge toward the *Maximum Theoretical Bias Possible* (1−1/N). Meanwhile, the Bias Level of the non-ideal elements, when converging to the minimum probability, should approximate the *Maximum Negative Bias Possible*, equal to the inverse of N.

28.5. Equality Models and Bias Tending Toward Zero

A model is described as an *equality model* when its objective is to ensure that all subjects or options within N converge equally toward the theoretical probability of 1/N.

In such a framework, the ideal is the realization of equality of opportunity: every subject or option has the same empirical probability. Consequently, the Bias Level for each element should tend toward zero, since empirical probability approaches theoretical probability.

The defining feature of equality models is therefore the minimization of individual deviations: the closer the Bias Level is to zero, the closer the system comes to embodying fairness and symmetry within the distribution.

28.6. The Zero Sample and the Distinction Between the First and Second Methods

Another noteworthy scenario occurs when the model assumes that the ideal is for the entire set N to converge equally toward an empirical probability of zero. This situation is referred to as the *zero sample model*. It provides one of the clearest demonstrations of the fundamental difference between the *First Method* of traditional statistics and the *Second Method* of Impossible Probability, specifically in how each interprets deviation.

In traditional statistics (the First Method), analysis is conducted using *direct scores*. The arithmetic mean is calculated as the average of these scores, and dispersion is

determined through the *differential score*—that is, the direct score of each subject minus the arithmetic mean.

Applied to a zero sample, traditional statistics would yield the following result: if every direct score equals zero, then the arithmetic mean is necessarily zero. Consequently, the differential score for each subject would also be zero, since each direct score (0) minus the mean (0) equals zero. As a result, the mean deviation of such a dataset would be zero.

In contrast, within the Second Method of Impossible Probability, a zero sample produces a radically different interpretation. Suppose that, by design, the ideal is that every subject or option has a direct score or frequency of zero (and therefore an empirical probability of zero). This might occur, for example, in the validation of a medical intervention where the empirical probability of contracting a disease after vaccination is expected to be zero, or in an industrial quality-control system where the probability of committing errors is expected to be zero.

In such cases, even if all empirical probabilities are zero, the *Mean Deviation of empirical probabilities* would not equal zero. Instead, it would equal the theoretical inverse of N (1/N). This is because the Bias Level for each subject, defined as empirical probability minus theoretical probability, would always equal the absolute value of /0−1/N/=1/N. Averaging this across all N subjects yields a deviation of exactly 1/N.

Thus, while traditional statistics would conclude that a zero sample exhibits no dispersion, Impossible Probability demonstrates that there is still deviation equals inversion of N, since it measures divergence not from an empirical mean but from the theoretical baseline of fairness. This reinterpretation underscores why, in Impossible Probability, *deviation* is reconceptualized as *bias*.

28.7. Mean Deviation in Impossible Probability as a Statistic of Bias

In the framework of Impossible Probability, the *Mean Deviation* of empirical probabilities acquires a distinctive interpretation when compared to traditional statistics. Consider a sample in which all empirical probabilities are equal to zero—a

so-called *zero sample*. In such a case, the Mean Deviation of empirical probabilities is not zero, as traditional statistics would dictate, but instead equals the inverse of N.

The reasoning is straightforward. If every empirical probability in the sample equals zero (and if this configuration is taken as the ideal outcome), then the *Bias Level* for each subject or option is simply the absolute value of the difference between the empirical probability (0) and the theoretical probability (1/N). This difference is always equal to 1/N. Since every element in the sample shares the same bias magnitude, the average (i.e., the mean deviation) of the sum of all these absolute bias levels is also 1/N.

This observation leads to an important reconceptualization. In traditional statistics (the First Method), the mean deviation of a zero sample is zero, because the calculation is performed around the arithmetic mean of the direct scores, which in this case is also zero. However, in Impossible Probability (the Second Method), deviation is not measured with respect to an arithmetic mean of frequencies, but with respect to the theoretical probability baseline. Consequently, deviation does not vanish but instead equals 1/N, which corresponds to the *Maximum Negative Theoretical Bias Possible*.

This reveals that what in Impossible Probability is called “Mean Deviation” is in fact not a deviation in the traditional sense, but rather a systematic measure of bias. It reflects the structural divergence between empirical behavior (here, zero probabilities) and the theoretical expectations of fairness or equal opportunity (given by 1/N). For this reason, Impossible Probability redefines deviation as *bias deviation*. This adjustment prevents the paradox of concluding that a sample of absolute zeros exhibits no dispersion, when in fact every element diverges maximally from the theoretical expectation.

28.8. Omega Models and Ideal Probability

Alongside positive bias models, equality models, and zero samples, there exists another class of idealized study models: the *omega models*. These emerge in situations where, given a total population N, there is a subset of ideal subjects or options larger than one but smaller than N.

An omega model is defined by the condition that more than one subject or option within N is considered ideal, but not all. In other words, the set N is composed of both ideal and non-ideal elements. For the model to qualify as a genuine omega model, the number of ideal elements must be at least two and at most N−1. Thus, there must always remain at least one non-ideal element (with the maximum being N−2 non-ideals).

In such models, the *ideal probability* for each ideal element is given by dividing unity by the number of ideals—represented mathematically as 1/Ω, inversion of omega, where Omega, Ω denotes the number of ideal subjects or options. The *Ideal Bias* in this case is defined as the difference between this ideal probability and the theoretical baseline of equal opportunity, 1/N.

Despite these variations, certain statistical principles remain constant across all models—positive bias, negative bias, equality, or omega. Specifically:

- The *Maximum Theoretical Bias Possible* is always 1−1/N.
- The *Maximum Negative Bias Possible* is always 1/N.
- The *Maximum Empirical Bias Possible* is equal to half of the total bias across the sample (i.e., *Total Bias ÷ 2*).
- The *Intermediate Dispersion* is always defined as half the difference between the maximum and minimum empirical probabilities.

The crucial difference lies in interpretation. While theoretical and negative maximum biases are defined relative to idealized models (e.g., privileging a single subject, or describing the bias of all non-ideals), the *Maximum Empirical Bias Possible* refers instead to the greatest bias an individual subject or option can achieve within a real empirical distribution. This is governed by the statistical law of compensation: all positive bias in a distribution necessarily offsets all negative bias, and vice versa.

This law of compensation—an axiom of statistical balance—guarantees that in any empirical system, the total magnitude of positive bias always equals the total magnitude of negative bias. Thus, even in extreme cases where an element approaches the Maximum Theoretical Bias, the aggregate of all other negative biases will precisely

counterbalance it. This property is fundamental to the coherence of Impossible Probability as a system, anchoring the relationship between theoretical models of bias and the empirical constraints of real distributions.

28.9. The Law of Bias Compensation and the Maximum Theoretical Mean Deviation Possible

A fundamental principle within Impossible Probability is the **law of statistical compensation of biases**. This principle asserts that in any distribution—regardless of the model employed—positive biases necessarily balance negative biases, and vice versa. It is an immutable rule: the statistical system is structured such that aggregate deviations in one direction must always be matched by aggregate deviations in the opposite direction.

This law implies that even if one subject or option in a given population reaches the *Maximum Theoretical Bias Possible*, the remaining N−1 non-ideal subjects will collectively exhibit negative biases whose sum equals this maximum positive bias. In other words, no matter how large a single positive deviation becomes, the system as a whole ensures exact counterbalancing through the negative deviations of all other elements.

From this observation follows a crucial consequence: the ability to calculate the **Maximum Theoretical Mean Deviation Possible**. Since the total system must always balance, the average of the doubled maximum theoretical bias necessarily equals this measure. Put differently, the statistical law ensures that, at the aggregate level, deviations distribute themselves symmetrically in such a way that the maximal positive deviation is compensated by the totality of negatives, yielding a computable upper bound for mean deviation.

Formally expressed:

$$\text{Maximum Theoretical Mean Deviation Possible} = \frac{(1 - 1/N) \cdot 2}{N}$$

This formula captures the essence of the law of compensation: statistical balance is not accidental but is inherent in the natural structure of probability. Positive and negative deviations exist in a state of systemic reciprocity, one perpetually counterweighing the other.

28.10. Maximum Empirical Bias Possible and the Distribution of Bias within the Sample

Building upon the law of bias compensation, we can identify the **Maximum Empirical Bias Possible** within any empirical distribution. This measure represents the greatest degree of deviation that any subject or option can attain in practice, given the actual arrangement of empirical probabilities within a sample.

The principle is straightforward: by summing the absolute values of all observed bias levels, we obtain the *Total Bias*. The Maximum Empirical Bias Possible is then defined as half of this quantity. Symbolically:

$$\text{Maximum Empirical Bias Possible} = \frac{\text{Total Bias}}{2}$$

This relationship arises from the statistical certainty that all positive biases are exactly counterbalanced by the aggregate of negative biases, and vice versa. Therefore, no individual subject can ever exceed half the total bias of the system. In this way, the Maximum Empirical Bias Possible constitutes a natural ceiling on deviation within any empirical distribution.

28.11. Intermediate Dispersion as a Relevant Statistic

Among the statistical instruments of Impossible Probability, the **Intermediate Dispersion** holds particular significance due to its conceptual simplicity and practical utility. It offers a quick yet meaningful approximation of the overall spread of empirical probabilities in a sample by focusing on the relationship between the maximum and minimum observed probabilities.

Intermediate Dispersion is defined as half the distance between the maximum empirical probability (p(xi+)) and the minimum empirical probability (p(xi−)). Closely linked to this is the concept of the *Intermediate Probability*, which is the mean of the maximum and minimum values:

$$\text{Intermediate Probability} = \frac{p(xi+) + p(xi-)}{2}$$

This measure provides an equidistant reference point between the extremes of the distribution, while the Intermediate Dispersion quantifies the “spread” between these extremes. Together, these statistics contribute valuable insight into the structure of the sample. Unlike traditional measures of central tendency, which focus on averages across all observations, these constructs emphasize the balance between extremes, aligning with the broader philosophy of Impossible Probability that prioritizes contrasts, deviations, and systemic compensation over simple aggregation.

28.12. Intermediate Probability as a Substitute for Empirical Central Tendency

The concept of **Intermediate Probability** acquires particular importance within the framework of Impossible Probability because of a structural limitation in the Second Method. Unlike traditional statistics (the First Method), which defines central tendency

through measures such as the mean, median, and mode, the Second Method lacks a distinct empirical central value. This absence arises because, in Impossible Probability, the arithmetic mean of the empirical probabilities is always equal to the theoretical probability (1/N).

In other words, the central value of empirical probabilities coincides with a theoretical construct rather than emerging directly from empirical distribution. Consequently, there is no uniquely empirical statistic capable of representing central tendency within the system. This limitation, however, does not imply a deficiency but instead highlights the methodological distinction between Impossible Probability and conventional statistics.

To address this absence, the **Intermediate Probability** (p(xi+/−)p) can be introduced as a substitute for empirical central tendency. Defined as half the sum of the maximum and minimum empirical probabilities, Intermediate Probability provides an approximate midpoint between the extremes of the sample:

$$p(xi+/-) = \frac{p(xi+) + p(xi-)}{2}$$

By situating itself between the observed boundaries of the sample, Intermediate Probability performs a role analogous to central tendency, though its logic is rooted in contrasts rather than aggregation. It therefore functions as a bridge statistic—one that allows empirical centrality to be estimated without abandoning the Second Method's theoretical alignment between averages and probabilities.

28.13. Relationships between Maximum, Minimum, Intermediate Probability, and Intermediate Dispersion

The relationship between **Intermediate Probability** and **Intermediate Dispersion** reveals an elegant symmetry within the statistical architecture of Impossible

Probability. While Intermediate Probability is defined as the equidistant point between the maximum and minimum empirical probabilities, Intermediate Dispersion is the half-distance between these two values. Taken together, these measures allow for the decomposition and reconstruction of the sample's extremes in a logically consistent manner.

Formally, the maximum empirical probability (p(xi+)) can be expressed as the sum of Intermediate Dispersion and Intermediate Probability, while the minimum empirical probability (p(xi−)) can be expressed as the difference between Intermediate Probability and Intermediate Dispersion:

$$p(xi+) = \frac{(p(xi+) - p(xi-))}{2} + \frac{(p(xi+) + p(xi-))}{2}$$
$$p(xi-) = \frac{(p(xi+) + p(xi-))}{2} - \frac{(p(xi+) - p(xi-))}{2}$$

These identities demonstrate that the extremes of a distribution (maximum and minimum) can be fully reconstructed by combining the midpoint (Intermediate Probability) with the half-distance between them (Intermediate Dispersion). In other words, the structure of the distribution can be expressed in terms of equilibrium and deviation.

This formulation underscores a core philosophical principle of Impossible Probability: that empirical reality is best understood not through isolated averages but through the dynamic interplay of contrasts. The maximum and minimum are not independent phenomena but are intrinsically linked by the symmetry of dispersion and the balance of centrality.

28.14. The Mean Deviation of Maximum and Minimum as an Empirical Limit

Just as one can calculate the **Intermediate Probability** (p(xi+/−)) by dividing by two the sum of the maximum and minimum empirical probabilities, or compute the **Intermediate Dispersion** by halving the difference between the maximum and the minimum, it is also possible to construct another limiting statistic. This consists of taking half the sum of the absolute values of the Bias Levels of the maximum and minimum. The resulting measure is known as the **Mean Deviation of Maximum and Minimum**, and it operates at the sample level as the **Maximum Empirical Mean Deviation Possible**.

The logic behind this designation is straightforward: within the framework of Impossible Probability, the empirical Mean Deviation of an entire distribution can never, under any circumstances, exceed the Mean Deviation of Maximum and Minimum. Thus, this measure provides a theoretical ceiling or limit for empirical deviation.

Formally expressed:

$$\text{Mean Deviation of Maximum and Minimum} = \frac{(p(xi+) - 1/N) + (1/N - p(xi-))}{2}$$

This formulation highlights a fundamental structural principle: the maximum deviation in a sample is constrained by the contrast between its extremes relative to the theoretical probability 1/N. By focusing on these two critical points—the highest and lowest probabilities—the statistic captures the boundary conditions within which all other empirical deviations must operate.

28.15. The Theory of Sample Statistics in the Second Method

From a methodological perspective, the construction of **sample-level statistics** within Impossible Probability follows a clear progression. Individual statistics—whether empirical or theoretical—form the foundation. From these, one derives **individual dispersion statistics** (again, either empirical or theoretical). Finally, by extension and

aggregation, one builds the **sample-level statistics**, which, by definition, are always measures of dispersion.

This approach differs significantly from traditional statistics, or the First Method. In classical frameworks, statistical measures are conventionally divided into two categories:

- **Measures of central tendency** (mean, median, mode).
- **Measures of dispersion** (mean deviation, variance, standard deviation).

By contrast, in the **Second Method of Impossible Probability**, while it is still possible to calculate analogues of central tendency (for example, the Intermediate Probability, p(xi+/−)), the real conceptual distinction lies not between *central tendency* and *dispersion* but rather between the **theoretical** and the **empirical**.

The reason is that dispersion and central tendency are not opposed categories in this system; rather, they are two poles of the same differential magnitude. Since all statistical magnitudes in Impossible Probability are expressed through differences—between empirical and theoretical probabilities, or between observed and ideal distributions—the underlying logic is always one of **dispersion**.

- If the scientific objective is **equality of opportunities**, then the ideal is that dispersion should tend toward zero.
- If the objective is the analysis of **bias** (positive or negative), then the ideal is a model of **maximum dispersion** according to the corresponding bias.
- If the model is **omega**, then the dispersion must be shaped according to the **ideal omega distribution**, where probabilities are equitably distributed among the subset of ideal subjects or options.

Thus, in Impossible Probability, the classification of statistics is guided not by the conventional central/dispersion dichotomy, but by the **orientation of the model** and the **objectives of scientific policy**. Before any hypothesis testing can take place, one

must establish both theoretical and empirical statistics to anchor the critique of reality within a defined rational framework.

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published in https://probabilidadimposible.blogspot.com/,
On 1 November 2012,
Rubén García Pedraza
imposiblenever@gmail.com

29. Sample Statistics

29.1. Individual Statistics in the Second Method

In the blog entry dated **October 20, 2012**, devoted to individual statistics, I offered an explanation of the different statistical measures that, within the framework of the **Second Method of Impossible Probability**, can be applied at the individual level. These were already extensively discussed in *Introduction to Impossible Probability: Statistics of Probability or Probabilistic Statistics*. Their function is to determine the **individual trend** of any given subject or option, regardless of the type of universe in which the analysis takes place.

The applicability of these statistics extends across all possible domains: universes of subjects or options, included finite populations, or universes of limited options. Whatever the case may be, the study of the **individual tendency** of each subject or option always begins with two foundational measures:

1. **Empirical Probability of a subject or option (p(xi))** – defined as the direct value or individual frequency divided by the total sum of direct values or frequencies in the system.

2. **Theoretical Probability (1/N)** – which corresponds to the inverse of the number of subjects or options, and which represents the probability that should apply if events occurred purely by chance under conditions of equal opportunity.

Together, these values allow for the calculation of the **Level of Bias**, defined as the difference between empirical probability and theoretical probability. The aggregation of the absolute values of all Levels of Bias yields what I call the **Total Bias**. From this, the **Maximum Empirical Bias Possible** can be derived, calculated as the Total Bias divided by two. This measure establishes an empirical upper limit, ensuring that no individual Level of Bias can surpass it.

The Second Method also introduces two further theoretical concepts. First, the **Maximum Theoretical Bias Possible**, which is defined as the difference between unity (representing the **Maximum Empirical Probability Possible**, or probability equal to one) and the theoretical probability (1/N). Second, the **Maximum Negative Bias Possible**, defined as the theoretical probability itself (1/N), and which applies particularly in models characterized by negative bias. These measures are part of the **multifunctional statistical tools** provided by the Second Method of Impossible Probability.

To provide further granularity:

- The **maximum empirical probability** of an entire sample, that is, the highest probability observed among all subjects or options, the empirical probability of the subject or option with the highest empirical probability in the sample, is denoted simply as the *maximum* (p(xi+)).
- The **minimum empirical probability**, the lowest empirical probability observed in the sample, is denoted as the *minimum* (p(xi–)).
- The **intermediate probability** is defined as the arithmetic average of the maximum and minimum probabilities ((p(xi+) + p(xi-)) : 2) .
- The **Intermediate Deviation** is defined as half the difference between the maximum and minimum ((p(xi+) – p(xi-)) : 2).
- Finally, if one takes half the sum of the absolute Levels of Bias of both the maximum and the minimum, this produces the **Mean Deviation of the Maximum and Minimum**, which functions as a critical boundary for empirical dispersion {[(p(xi+) – 1/N) – (p(xi-) – 1/N] : 2}.

In the particular case of **omega models**, where the universe *N* contains an *ideal subset* of subjects or options greater than one but fewer than *N* (that is, ranging between two and *N – 1*), the **ideal probability** is defined as the inverse of omega (1/Ω). Correspondingly, the **Ideal Bias** is defined as the difference between the inversion of omega and the inversion of N. This formulation allows omega models to articulate a distinct standard for individual ideality and its measurement of deviation.

29.2. Classification of Individual Statistics

From the standpoint of Impossible Probability, **individual statistics** can be classified into four major categories:

1. **Empirical Individual Statistics** – These describe the actual, observed behavior of a specific subject or option within a given sample. They capture the contingent and historical reality of the subject's behavior in relation to the broader system.
2. **Theoretical Individual Statistics** – These are normative or idealized measures, indicating how a subject or option *should* behave according to the objectives and orientation of scientific policy. They serve as a benchmark for rational critique and for the construction of critical probability.
3. **Empirical Individual Dispersion Statistics** – These indicate how the observed behavior of a subject or option compares with that of the entire sample, measuring the extent of deviation or spread at the individual level.
4. **Theoretical Individual Dispersion Statistics** – These are the expected or ideal patterns of dispersion that each subject or option should display, as determined by the philosophical and political ideals underpinning scientific policy.

In this sense, the classification reflects the dual structure of Impossible Probability, which constantly balances between **empirical reality** (what is observed) and **theoretical ideals** (what should be, according to rational or normative models). Each individual statistic thus functions as a node in the broader system of rational critique: empirical statistics record actual tendencies, theoretical statistics project normative ideals, and dispersion statistics—both empirical and theoretical—evaluate the degree to which these tendencies converge or diverge.

[For this reason, if we can name one, 1, as Maximum Possible Empirical Probability, in reality is a theoretical value, actually sometimes I call it Maximum Possible Theoretical Probability, it is just the upper limit in any probability. While probability = 1 can be

interpreted as a theoretical value, the same can be applied for probability = 0 as Minimum Possible Empirical Probability, it is just the lower limit, therefore it is a theoretical value. If one and zero are theoretical values, the empirical values corresponds to : the subject or option in the sample with the highest empirical probability, the maximum empirical probability in the sample (p(xi+)), and the subject or option with the minimum empirical probability, the lowest empirical probability in the sample (p(xi-)).]

29.3. Rational Critique of Individual Tendencies

Once the individual and dispersion statistics—both **empirical** and **theoretical**—have been established in accordance with the objectives of scientific policy, the next step is to determine whether the trend of a given subject or option can be considered rational. This determination is carried out through what I term the **rational critique of empirical tendencies**.

In this framework, rational critique functions as the confrontation of **empirical behavior** with its **theoretical counterpart**, always evaluated under the light of *critical reason*. The role of critical reason here is crucial: it defines the acceptable **margin of error** that scientific policy is willing to tolerate in order to pursue its broader objectives and ideals.

So far, in this blog, the rational critique of individual tendencies has focused primarily on **differential relations** between empirical and theoretical statistics. These models include the tests of **Validity** or **Significance** in relation to **Equality**, **Positive Bias**, or **Negative Bias**. In addition, within the special class of **omega models**, one encounters their corresponding criteria: **Omega Validity** and **Omega Significance**.

However, this constitutes only a partial view of the broader spectrum presented in *Introduction to Impossible Probability: Statistics of Probability or Probabilistic Statistics*. In that more extensive work (specifically in section eleven), I also develop additional models that go beyond differential comparisons. These include **quotient relations** between empirical and theoretical statistics, not only at the individual level

but also at the **sample level**. This expansion underscores the versatility of Impossible Probability: it is not limited to assessing how much empirical behavior differs from theoretical expectations, but also examines their proportional relations, thereby enriching the logic of rational critique.

In sum, the rational critique of individual tendencies in Impossible Probability represents a systematic effort to confront **what is observed** with **what is theoretically expected**, under the explicit constraints of critical reason and the ideological goals of scientific policy.

29.4. Models of Rational Critique at the Individual Level

In the context of Impossible Probability, what traditional statistics usually calls **hypothesis testing models** are instead referred to as **models of rational critique**. This terminological shift is intentional and reflects the philosophical foundation of the theory. Whereas in conventional statistics hypothesis testing is understood as the confrontation of data with a null hypothesis, here the focus is broader: the rational critique is the confrontation of **empirical and theoretical behavior** through the interpretive lens of **critical reason**.

The fundamental aim is always the same: to assess whether a given individual trend is **sufficiently rational** to be accepted, even provisionally, as part of scientific theory. Thus, a model of rational critique at the individual level evaluates whether a single subject or option behaves in such a way that its observed empirical tendency can be deemed rational according to the normative standards of scientific policy.

However, the acceptance of a hypothesis—whether **explanatory** (aimed at understanding reality) or **technological** (aimed at validating practical interventions)—cannot rest solely on the rationality of an individual subject's behavior. It must also be verified that the same rationality is reflected at the **sample level**. Otherwise, scientific decisions would be at risk of error, either through misjudging the acceptable error margin defined by critical probability in the individual critique, or through overlooking the statistical implications of the **sample size** (N). This applies equally to universes of

subjects and options—whether infinite, population-based, or limited to frequencies and direct scores.

Therefore, the Second Method of Impossible Probability establishes a dual requirement:

1. **Individual Rationality** – A tendency must first be rational at the level of the individual subject or option, as measured against the theoretical models and critical margins established by scientific policy.
2. **Sample Rationality** – That same tendency must then be confirmed at the level of the sample as a whole. Only when individual rationality converges with sample rationality can an empirical hypothesis—whether explanatory or technological—be elevated to the status of a **rational hypothesis**.

Once accepted, such a hypothesis provisionally enters the **domain of scientific theory**. Its acceptance is universal in scope but provisional in nature: universal because it applies to the scientific community at large, but provisional because it remains subject to future critique, refutation, or replacement as new margins of error and new models emerge.

[This sentence, *"Once accepted, such a hypothesis provisionally enters the domain of scientific theory,"* only reflects the way human science works. In GAI, theory is replaced directly by rational truth, serving only to build the global model, and beyond the sixth phase, to integrate the Global Project System (GPS) within the Global Artificial Intelligence.]

29.5. From Hypothesis to Theory and Paradigm

The rational acceptance of an empirical hypothesis, or of a set of interrelated hypotheses, can serve as the foundation for the construction of a **scientific theory**. A theory, in turn, may encompass and systematize multiple hypotheses under a coherent conceptual and mathematical framework. Several scientific theories, once

consolidated, may converge into what we call a **scientific model**—a structured body of knowledge that not only explains but also predicts and guides research within a defined field. Finally, one or more models can culminate in the constitution of a **scientific paradigm**.

A paradigm should not be understood merely as a theoretical structure but as the **dominant framework** within which a scientific community interprets phenomena, formulates problems, designs experiments, and evaluates results. In this sense, the acceptance of hypotheses and their progressive articulation into theories, models, and paradigms represents the ascending hierarchy of scientific rationality. This hierarchy is at once logical, epistemological, and political, since the consolidation of a paradigm is also a process of **universal recognition and provisional legitimation** by the broader scientific community.

Whether in the form of a paradigm for a single science or a paradigm that extends across multiple sciences, the progression from hypothesis to theory and to paradigm demonstrates how **individual rational critiques** accumulate into a wider, shared system of knowledge, always provisional but necessary for the advancement of science.

29.6. Provisionality and the Limits of Every Hypothesis

The rational acceptance of a scientific hypothesis is always **universal but provisional**. It is universal because, once validated, it is recognized across the scientific community; but it is provisional because it is subject to revision or rejection when the **margins of error** initially accepted become inevitable over time.

These margins of error operate at several levels:

- The **critical probability**, which expresses mathematically the critical reason chosen by scientific policy, defines the acceptable error when comparing empirical and theoretical values, whether at the individual or sample level.

- The **sample size (N)**, whether in infinite universes of subjects and options, population-level universes, or universes of limited options, determines the degree of reliability but also implies a corresponding margin of error.

Even if a hypothesis is accepted rationally, based on criteria that grant it a very high or even total degree of provisional reliability, the inevitability of error will surface when sufficient time—or even an infinite horizon—is considered. At that point, a hypothesis once deemed provisionally rational must be rejected.

Scientific policy must then resolve the problem by formulating a **new hypothesis**. This new proposal must aim to be more reliable by reducing error margins—both those related to critical probability and those associated with sample selection. In this way, science progresses: not by eliminating error entirely, which is impossible, but by continuously **reducing the logical incoherence** between two poles: the *moral truth in itself* (reality as it exists independently of us) and the *political truth for itself* (the provisional truths accepted by science).

[Even if a Global AI were able to make scientific statements with a margin of error equal to zero, it would still face the margin of error associated with the inversion of the sample.]

29.7. The Eternal Scientific Return and the Inevitability of Error

Scientific progress thus unfolds as a series of **crises and revolutions**. Errors that were once acceptable under a given paradigm eventually accumulate until they become unsustainable. At that point, science undergoes a **scientific revolution**, replacing old hypotheses, theories, and models with new ones that offer greater reliability. Over time, this process accelerates, approaching what can be described as a paradigm of **Permanent Scientific Revolution**.

However, even within this accelerating cycle, a fundamental principle must be acknowledged: **no hypothesis can ever fully escape error**. No matter how small the margin of error accepted by scientific policy—even if it tends toward zero—it can never be completely eliminated. The central thesis of Impossible Probability asserts that a

possibility, however improbable or even seemingly impossible, can nevertheless become **inevitable** within a sufficient or infinite timeframe.

Mathematically, this means that even if the accepted error approaches zero—represented as "(1/N = 0.0000...) – 0 = 0"—the possibility of error still persists as a logical inevitability. Thus, every hypothesis, no matter how rigorously validated, remains subject to eventual falsification.

Consequently, in the long run, **all scientific hypotheses are false**. Their truth is only provisional, granted universal rational acceptance for a time but destined, given infinite time, to collapse under the weight of error. Each hypothesis, once discarded, must be replaced by new ones that reduce error margins and increase reliability—yet these, too, are destined to fail eventually.

This cycle—the **eternal scientific return**—is not a mark of weakness but the very mechanism of scientific progress. It ensures that science continuously evolves, enhancing the reliability of its theories while fully embracing the provisional nature of its truths. In this way, error is not merely a threat but a **structural condition** of knowledge, the very driver of the self-correcting process by which science advances.

29.8. *Impossible Probability* as a Modern Theory

In this sense, *Impossible Probability* can be considered a modern theory, insofar as it shares with positivism the need to ground science in the isomorphism between science and reality itself. For this reason, the progress of science is understood as the progress in its reliability, aimed at reducing the incoherence between scientific theory and reality in itself. At the same time, *Impossible Probability* shares with Kantian critical rationalism the conviction that reality in itself is unknowable: we will never fully know the *noumenon*. Therefore, everything must remain subject to rational doubt and empirical skepticism. The margin of error of critical probability thus expresses the margin of doubt and skepticism of critical reason.

At the same time, *Impossible Probability* also shares with the dialectical materialism of Marx and Engels the principle that every scientific construction is ultimately an

ideological construction of reality. In modern science, everything depends on scientific policy, which is itself determined by the political ideology underlying science. Thus, every paradigmatic struggle—whether in a particular discipline or in science as a whole—is, at its core, a struggle between different models of understanding scientific policy, consistent with their ideological differences. A Scientific Revolution occurs when one such model is universally and provisionally accepted as the paradigm, either of a particular science or of all the sciences. This universal acceptance lasts until the errors admitted by the critical reason of that paradigm inevitably manifest. At that point, a new paradigmatic crisis arises, one that can only be overcome through the establishment of a new paradigm. The defining quality of this new paradigm must be its ability to further advance the reliability of science.

If science maintains this trajectory, it may reach the paradigm of Permanent Revolution. However, should science stagnate—whether in a prolonged paradigmatic struggle or in a paradigm that, despite admitting a high margin of error and having its errors demonstrated, is nevertheless preserved by scientific policy for purely ideological reasons—a paradigmatic crisis will inevitably result. Such a crisis can only be overcome through a true Scientific Revolution capable of resolving the stagnation and continuing the progress of scientific reliability.

29.9. Sample Statistics and Their Critical Necessity

For an individual trend to be rationally accepted, it is necessary to examine the different individual statistics, including measures of dispersion, which must be subjected to rational critique—whether in terms of validity or significance, equality or bias, positive or negative, or within omega models—so that the individual trend may be confirmed at the sample level. For this reason, it is also necessary to subject sample statistics to rational critique, in order to determine their validity or significance, their equality or bias, or their behavior within omega models, at the level of the sample.

Therefore, before introducing the explanation of some of the models of rational critique at the sample level presented in *Introducción a la Probabilidad Imposible*, it is important to first define what is meant by sample statistics. A statistic is understood as

the quantitative value of a trend, which, in this case, describes the behavior of the sample trend.

Within sample statistics, a further distinction must be made between *empirical sample statistics* and *theoretical sample statistics*, rather than following the classical division between measures of central tendency and dispersion. In *Impossible Probability*, what matters most is not whether a statistic describes central tendency or dispersion, but rather whether it is theoretical or empirical. From the contrast between these two, under the light of critical reason, the models of rational critique—at the sample level—will be determined, whether they concern differential relations or ratios between empirical and theoretical statistics.

29.10. Empirical Sample Statistics

In the framework of *Impossible Probability*, the traditional sample statistics are reinterpreted and reformulated. In classical statistics—what we have been calling the First Method—the main empirical sample statistics are the **Mean Deviation**, **Variance**, and **Standard Deviation**. These are normally computed over **differential scores**, i.e., the deviation of each observed value from the arithmetic mean.

By contrast, in the Second Method proposed in *Impossible Probability*, these same measures are recalculated not on differential scores but on the **Levels of Bias**—defined as the difference between the empirical probability and the theoretical probability (1/N). This conceptual shift produces significant consequences for probabilistic statistics.

For instance, in traditional statistics, if we are given a **zero sample**—that is, a set of direct scores or frequencies that are all equal to zero—the resulting Mean Deviation, Variance, and Standard Deviation are also zero. In Impossible Probability, however, when the sample consists of probabilities all equal to zero, the results are radically different:

- The **Mean Deviation** of empirical probabilities equals the **inverse of N (1/N)**.
- The **Variance** equals the square of the inverse of N.

- The **Standard Deviation** equals the square root of the variance, which again yields the inverse of N.

Formally, the formulas for these statistics in Impossible Probability are expressed as follows:

- **Mean Deviation**: the average of all Levels of Bias, that is, the mean of the absolute differences between empirical and theoretical probabilities:

$$\text{Mean Deviation} = \frac{\Sigma\,|p(x_i) - 1/N|}{N}$$

- **Variance**: the average of the squared Levels of Bias:

$$\text{Variance} = \frac{\Sigma\,(p(x_i) - 1/N)^2}{N}$$

- **Standard Deviation**: the square root of the variance:

$$\text{Standard Deviation} = \sqrt{\frac{\Sigma\,(p(x_i) - 1/N)^2}{N}}$$

Beyond these classical statistics, the Second Method introduces **complementary measures**, derived from its own theoretical developments, such as the **Intermediate Deviation** and the **Mean Deviation of Maximum and Minimum**. These measures provide alternative and often more intuitive ways of quantifying dispersion in a sample.

The **Intermediate Deviation** is calculated as one half of the difference between the maximum and the minimum empirical probabilities:

$$\text{Intermediate Deviation} = \frac{p(x_i^+) - p(x_i^-)}{2}$$

Its value provides a **quick reference to the dispersion** between the most extreme values in the sample. It can be interpreted both as an *individual dispersion statistic* (since it concerns the two most extreme probabilities individually) and as a *sample dispersion statistic* (since it characterizes the distribution as a whole).

The **Mean Deviation of Maximum and Minimum** averages the absolute Levels of Bias of the maximum and minimum empirical probabilities:

$$\text{Mean Deviation of Maximum and Minimum} = \frac{|p(x_i^+) - 1/N| + |p(x_i^-) - 1/N|}{2}$$

This measure is particularly relevant because it establishes an **empirical upper bound** for the Mean Deviation of the sample. In fact, the Mean Deviation can never exceed the Mean Deviation of Maximum and Minimum. For this reason, it can be considered the **Maximum Empirical Mean Deviation Possible**, serving as a useful benchmark when analyzing the empirical distribution of probabilities in a sample.

In short, while traditional statistics are centered on central tendency and standard measures of dispersion, the Second Method of Impossible Probability reinterprets these tools by anchoring them in **empirical vs. theoretical probability differentials**. This not only provides new statistical insights but also allows for complementary measures—Intermediate Deviation and Mean Deviation of Maximum and Minimum—

that enrich the analysis of dispersion within samples and extend the interpretative capacity of probabilistic statistics.

29.11. Theoretical Sample Statistics

The **theoretical sample statistics** in *Impossible Probability* have already been presented in earlier sections of this blog, and they also appear in *Introduction to Impossible Probability: Statistics of Probability or Probabilistic Statistics* in several places. These statistics represent the *idealized upper bounds* of dispersion measures, serving as theoretical limits against which empirical behavior can be evaluated. In essence, they include:

1. the **Maximum Theoretical Mean Deviation Possible**,
2. the **Maximum Theoretical Variance Possible**,
3. the **Maximum Theoretical Standard Deviation Possible**, and, once the **Intermediate Deviation** and the **Mean Deviation of Maximum and Minimum** are incorporated into the system, additional theoretical maxima for these measures as well.

These statistics allow us to establish what the *greatest possible tendency* would be if the distribution of probabilities reached its most extreme theoretical conditions.

29.11.1. Maximum Theoretical Mean Deviation Possible

This statistic is defined as the average of twice the **Maximum Theoretical Bias Possible**. Since the Maximum Theoretical Bias is given by 1−1N1 - \tfrac{1}{N}1−N1, the formula becomes:

$$\text{Maximum Theoretical Mean Deviation Possible} = \frac{(1 - \frac{1}{N}) \cdot 2}{N}$$

This expression represents the greatest possible mean dispersion, under idealized conditions, across all subjects or options within a sample of size N.

29.11.2. Maximum Theoretical Variance Possible

The Maximum Theoretical Variance Possible is defined as the average of the sum of two terms:

- the square of the Maximum Theoretical Bias Possible, and
- the product of the square of the inverse of N multiplied by N−1, which accounts for all the non-ideal cases in the distribution.

The formula is therefore:

$$\text{Maximum Theoretical Variance Possible} = \frac{(1 - \frac{1}{N})^2 + \left(\frac{1}{N}\right)^2 \cdot (N - 1)}{N}$$

This result gives the theoretical upper bound for variance in the system, ensuring that any empirical variance must necessarily remain below or equal to this threshold.

29.11.3. Maximum Theoretical Standard Deviation Possible

The Maximum Theoretical Standard Deviation Possible is simply the square root of the Maximum Theoretical Variance Possible:

$$\text{Maximum Theoretical Standard Deviation Possible} = \sqrt{\frac{(1-\frac{1}{N})^2 + \left(\frac{1}{N}\right)^2 \cdot (N-1)}{N}}$$

This measure allows us to anchor empirical standard deviations within an idealized limit, thereby defining the maximum possible spread of probabilities consistent with the laws of the system.

29.11.4. Maximum Theoretical Intermediate Deviation Possible

The **Intermediate Deviation** is defined as half the difference between the maximum and the minimum empirical probabilities. In theoretical terms, under a positive-bias model, the maximum probability equals the **Maximum Empirical Probability Possible (1)** and the minimum equals the **Minimum Empirical Probability Possible (0)**. Under this extreme condition, the Maximum Theoretical Intermediate Deviation Possible is simply:

$$\text{Maximum Theoretical Intermediate Deviation Possible} = \frac{1-0}{2} = 0.5$$

This value of 0.5 therefore represents the absolute theoretical ceiling for Intermediate Deviation.

29.11.5. Maximum Theoretical Mean Deviation of Maximum and Minimum

Finally, the **Mean Deviation of Maximum and Minimum** can also be extended to its theoretical maximum. If the maximum probability tends to 1 (Maximum Empirical Probability Possible) and the minimum tends to 0 (Minimum Empirical Probability Possible), then the Maximum Theoretical Mean Deviation of Maximum and Minimum equals half the sum of the Maximum Theoretical Bias Possible and the Maximum Negative Theoretical Bias Possible:

$$\text{Maximum Theoretical Mean Deviation of Maximum and Minimum Possible} = \frac{(1 - \frac{1}{N}) + \frac{1}{N}}{2} = 0.5$$

Interestingly, this result shows that the Maximum Theoretical Intermediate Deviation Possible and the Maximum Theoretical Mean Deviation of Maximum and Minimum coincide, both yielding a value of 0.5. This equivalence underlines the internal coherence of Impossible Probability: no matter which statistical lens is applied to the extreme case, the theoretical ceiling remains the same.

In conclusion, the theoretical sample statistics in Impossible Probability function as **absolute upper bounds** that anchor the empirical analysis. They reveal what the dispersion would be under extreme and idealized distributions of probability, and they serve as indispensable reference points for rational critique. By contrasting empirical values with these theoretical maxima, one can evaluate whether an observed trend remains within acceptable margins of error, thereby aligning scientific policy with the principles of critical reason.

29.12. Differential Relations and Critical Proportions

Within the framework of *Impossible Probability*, the relationship between empirical and theoretical values can be constructed in two fundamental ways.

1. **Differential relations**: where the empirical value is compared to its theoretical counterpart through subtraction (empirical value minus theoretical value).
2. **Proportional relations**: where the empirical value is compared to the theoretical value through division (empirical value divided by theoretical value).

Once either of these relationships is established, the **syllogism of tendency** is applied. This procedure examines whether the observed relation—whether differential or proportional—reveals a discernible trend. On the basis of this trend, one can then determine the **maximum theoretical statistics** that represent the extreme boundaries of dispersion or bias. These theoretical maxima serve as the ultimate reference points upon which *critical reason* operates. The acceptance of a margin of error relative to these maxima, mathematically expressed as **critical probability**, defines the rational threshold upon which scientific policy rests.

Up to this point in the blog, the emphasis has been placed on the **differential relations** between empirical and theoretical statistics, particularly at the individual level. This includes measures of **Validity or Significance**, whether of **Equality** or **Bias**, **Positive or Negative**, as well as the special cases of **Omega Validity** or **Omega Significance**. These models allow us to assess whether an individual empirical tendency deviates from its theoretical counterpart within an acceptable margin, thereby determining whether it can be considered rational.

However, the broader theoretical system of *Impossible Probability*, as elaborated in *Introduction to Impossible Probability: Statistics of Probability or Probabilistic Statistics* (specifically in Section Eleven), also extends the logic of rational critique to **proportional relations**. In this case, instead of subtracting the theoretical value from the empirical, one constructs a ratio by dividing the empirical value by its theoretical

equivalent. These ratios are referred to as **proportions**, and when they are subjected to rational critique, they become known as **critical proportions**.

Critical proportions function analogously to differential relations, but they often provide a more nuanced understanding of how close or distant an empirical observation is from its theoretical expectation. Whereas differential relations highlight the absolute gap between empirical and theoretical tendencies, proportional relations focus on the *relative magnitude* of these differences. Both approaches are indispensable: the differential relation underscores deviation in absolute terms, while the proportional relation measures deviation in relative or multiplicative terms.

At this stage of exposition, the blog has not yet offered a systematic development of critical proportions. For didactic reasons, the focus remains on consolidating the foundations of rational critique through **differential relations**. Therefore, the present distinction between **empirical sample statistics** and **theoretical sample statistics** serves as the framework within which differential relations are analyzed across entire samples. Critical proportions will be addressed subsequently, as part of the broader effort to integrate both differential and proportional reasoning into the full logic of *Impossible Probability*.

By establishing this dual framework of differential and proportional critique, *Impossible Probability* strengthens its epistemological foundations. It does so by ensuring that both the *absolute* and *relative* dimensions of divergence between empirical data and theoretical models are accounted for, always under the governance of critical reason and the margins of error defined by scientific policy.

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Rubén García Pedraza
imposiblenever@gmail.com

30. The Syllogism of Tendency

30.1. Initial Epistemological Differentiation

In the positive, rational, and moral or political development of the *statistics of probability* or *statistical probability*—a framework here designated as *Impossible Probability*—it is essential to distinguish, in epistemological terms, between two different levels of methodology. On the one hand, there is the practical methodology that entails the use of statistical techniques within the empirical sciences, both natural and social [and technological withing GAI]. On the other hand, there is the deeper scientific method required for the internal development of statistics and probability as a discipline in their own right. This latter method cannot be borrowed from the empirical sciences themselves but must necessarily be rooted in logic, and within logic, more specifically in the form of reasoning known as the *syllogism*. In the particular case of Impossible Probability, this takes the specific form of the *syllogism of tendency*, which becomes the structural foundation for deriving rational conclusions about empirical phenomena.

30.2. Impossible Probability as a Critical Mathematical Theory

The *statistics of probability*—or *Impossible Probability*—presents itself as a rationally critical mathematical theory. Its role is not merely to provide descriptive tools for data analysis but to construct a framework of heuristic methods that allow for the rational critique of empirical sciences. These heuristic instruments are articulated through three core methodological innovations: the *Impact of the Defect*, the *Second Method*, and the *Effective Distribution*. Each of these contributes to the establishment of rational, logical, and also moral or political criteria. The purpose of such criteria is to

evaluate whether an empirical hypothesis may be provisionally accepted as rational or, conversely, whether it ought to be rejected. By embedding moral-political considerations into the logical framework, Impossible Probability emphasizes that scientific acceptance always occurs within a broader epistemological and ethical horizon.

30.3. Distinction Between Empirical Methodology and Formal Development

From this perspective, it becomes clear that one must epistemologically differentiate between two distinct uses of statistics of probability. The first is its function as a heuristic methodology employed by empirical sciences to subject their hypotheses to rational critique. The second is its function as a formal logical method guiding the internal theoretical development of statistics of probability itself, considered as a self-standing mathematical discipline. Impossible Probability emphasizes that confusing these two planes leads to epistemological error: whereas empirical sciences require tools for testing hypotheses against reality, the development of the discipline of probability and statistics demands a method capable of generating new theoretical propositions. That method, as argued here, is precisely the syllogism of tendency.

30.4. The Second Method Explained

Within Impossible Probability, various heuristic research methods have been formulated to assist the growth of empirical sciences. Of these, the *Second Method* currently occupies central explanatory attention. This method begins from the concept of *empirical probability of a subject or option*. With this as its base, it undertakes a rational critique of the hypotheses advanced by empirical sciences. Its goal is to determine whether the tendencies affirmed by one or several hypotheses are rationally strong enough to be provisionally accepted as universal, though always within the limits of an error margin determined by the prevailing scientific policy. Only when a hypothesis satisfies this threshold can it be temporarily integrated into the body of scientific theory that undergirds a given scientific policy. Thus, the Second Method exemplifies the way

in which Impossible Probability establishes a bridge between empirical evidence and rational acceptance, constantly mediated by the dialectic of probability, logic, and political judgment.

30.5. Difference Between Empirical Critique and the Syllogism of Tendency

When the distinction is drawn between (a) statistics of probability as a method of rational critique within the empirical sciences, and (b) the method used for the theoretical development of statistics of probability itself—the syllogism of tendency—what emerges is an explicit epistemological differentiation. On one side stand the methodologies of empirical sciences, whether natural or social [or technological], which rely on heuristic instruments for interpreting phenomena. On the other side stand the methodologies for the development of non-empirical or formal sciences, namely logic and mathematics, within which Impossible Probability situates itself. The syllogism of tendency thus functions not as a heuristic device but as the internal logical mechanism that allows statistics of probability to progress as a formal science in its own right, generating universal formulations from rigorously deduced premises.

30.6. Overcoming the Distinction Between Social and Natural Sciences

What follows from this argument is that the traditional division between methods belonging to the natural sciences and those belonging to the social sciences is not logically sustainable from a positive and rational perspective. Both sets of disciplines share the defining condition of being empirical sciences. Thus, the boundary historically drawn between them is more the product of convention than epistemological necessity. From the standpoint of dialectical logic, the distinction is even less adequate, because the relationship between quantitative and qualitative approaches is itself dialectical. Quantitative data inevitably transform into qualitative insights, while qualitative analysis often generates new quantitative parameters. This mutual transformation—long emphasized by thinkers such as Hegel, Marx, and Engels—demonstrates that the rigid separation of natural sciences (quantitative) and

social sciences (qualitative) overlooks the deeper unity of scientific method when considered at the empirical level.

[While Marxism has always distinguished between dialectical materialism and historical materialism, Marx and Engels defended the idea that the quantitative transforms into the qualitative and vice versa. From our point of view, there is no difference in the methodology used for natural sciences and social sciences [this is part of our positivist legacy], as long as both are founded on the hypothetical-deductive method. Moreover, from our perspective, there is no reason to separate social studies from natural studies: the study of human society, even with all its complexity, is ultimately the study of a phenomenon produced by natural evolution: humans are part of the natural history. The difference is that humans represent a unique risk in the natural history of our planet, not only because of the challenges posed by pollution and environmental issues, but also because of their potential for self-destructive behavior.

Something we must keep in mind while replicating human rationality in AI is the need to reproduce the most productive and positive essence of humanity, not its self-destructive tendencies. This means that research on Artificial Emotional Intelligence could be key in the development of a highly resilient AI—one not only capable of surviving in any environment, but also of avoiding self-destruction.]

30.7. The Dialectic Between the Quantitative and the Qualitative

In reality, there is no inherent contradiction between the use of statistical methods for the rational critique of phenomena and the use of qualitative methods for their interpretation. Apparent contradictions typically arise only when political or ideological interests intervene, shaping the “scientific policy” in ways that lead to conflicting conclusions. At its core, however, quantitative analysis always demands interpretation, and every reading of a statistical table is inescapably a hermeneutic act. This means that statistical data do not “speak for themselves”; they must be read within a framework of meaning. The moral task of science, therefore, is to transform this interpretive necessity into an exercise of rational objectivity. Unlike purely subjective interpretation, moral interpretation within science seeks to minimize political error in

the evaluation of reality, thereby enhancing the reliability of scientific conclusions. To achieve this, rational criteria are set for the critique of reality through hypothesis testing. By accepting a morally permissible margin of error, science negotiates the gap between two poles: the moral truth of reality itself and the moral truth constructed by scientific policy.

30.8. Hypothesis Testing as a Control of Moral Error

Hypothesis testing, under this framework, becomes a mechanism for controlling moral error, including the error that might arise from the subjective involvement of the researcher in the research process itself. Its role is to safeguard the highest degree of moral reliability—that is, scientific reliability—that a given scientific policy is prepared to accept. Politically, this translates into the willingness to tolerate only the smallest possible margin of error. Logically, however, if everything that can possibly happen—including error—must eventually occur given sufficient or infinite time, then any rational acceptance of an empirical hypothesis can only ever be provisional and universal in a temporary sense. This is where the moral uncertainty of science arises.

Far removed from Kant's first categorical imperative, modern science cannot establish the kind of universally binding maxims that Kant desired, analogous to the laws of Newtonian physics that apply across all possible times. Modern science can only arrive at maxims that are morally universal in a provisional sense. In this respect, Impossible Probability, as a form of critical rationalism, converges with Popper's falsificationism in the recognition that science can never claim to be absolute but only provisional, always open to revision and correction.

30.9. Provisional Science and Critical Rationalism

If early critical rationalism, as represented by Kant, along with the first positivism of Comte and the dialectical materialism of Marx and Engels, sought a science grounded in universal maxims—as demanded by the Kantian imperative for moral universality, or in the form of Newtonian laws valid across all historical epochs, past, present, and

future—then history has shown otherwise. The evolution of positivism, critical rationalism, and dialectical materialism diverged significantly from this ideal.

The logical positivism of the Vienna Circle, the empirical and critical rationalism of Wittgenstein and Popper, particularly in light of the contradictions revealed in quantum mechanics and astrophysics, and the later evolution of dialectical materialism in the Frankfurt School—all testify to the erosion of the hope for universal and timeless scientific laws. The critical paradigm and subsequent alternative theories influenced by Horkheimer, Adorno, Marcuse, and Fromm underscored the impossibility of founding science upon universal, space-time invariant laws.

Thus, contemporary empirical science is characterized by its provisionality. It operates within a framework of rational doubt and empirical skepticism, a constant exercise of rational critique that defines the margin of error acceptable to scientific policy. Science, in this light, is neither absolute nor final, but an ongoing, provisional endeavor, always subject to revision in the face of new evidence or rational critique.

[The fact that science cannot provide universal and eternal truths beyond a limited period of provisionality could be interpreted as one of the powerful reasons for the rise of postmodernism and relativism. At some point, together with Gödel's theorem, this was also the position of the later Wittgenstein: if there is no definitive way to validate empirical propositions, then there is no way to justify the superiority of mathematics—it is, in the end, just another language]

30.10. Convergence of Positivism, Critical Rationalism, and Dialectical Materialism

Within the framework of *Impossible Probability*, there is no room for debate over whether a contradiction exists between the qualitative and the quantitative, or between the natural and social sciences. From its theoretical perspective, conceived as a synthesis of *positivism*, *critical rationalism*, and *dialectical materialism*, such oppositions lose their significance. What unites all sciences—whether natural or

social—is their empirical character. As empirical sciences, they are bound by the same obligation: to be rationally critical.

This obligation requires that they employ methods designed to minimize possible error, thereby strengthening the reliability of science itself. By reducing the margin of error, empirical sciences increase the reliability of their rational hypotheses. Scientific progress, therefore, unfolds as a continuous movement through cycles of crisis and scientific revolution, in which empirical theories are provisionally accepted, tested, refined, and eventually superseded. Within this process, Impossible Probability situates itself as a unifying epistemological framework, providing the logical structure by which empirical sciences can advance rationally.

Nevertheless, an important epistemological distinction must always be maintained: the distinction between statistics and probability as methodologies for advancing empirical sciences, and statistics and probability as disciplines that employ their own internal method—the *syllogism of tendency*—to develop as sciences in their own right.

30.11. Differentiation Between Applied Mathematics and Mathematics Itself

This distinction leads us to a more general epistemological clarification: mathematics must be understood in two distinct senses. On one level, mathematics functions as the quantitative language of the empirical sciences. In this role, it offers heuristic methods to all other empirical disciplines, both natural and social, thereby serving as a tool for their development. On another level, however, mathematics is not merely a language applied externally but is itself the object of scientific study.

The difference can be clarified through analogy with linguistics. A natural language, such as Spanish or English, can serve as the medium for developing knowledge in fields as diverse as law, history, or physics. Yet beyond its instrumental function, there exists a discipline—linguistics—that studies language in and of itself. Similarly, while mathematics supports the progress of the empirical sciences as a universal language of quantification, there is also the field of mathematics considered in itself, with its own internal problems, methods, and theoretical development.

Impossible Probability positions statistics and probability within this second sense: not simply as applied tools for empirical research, but as sciences in their own right that require an internal methodological foundation.

30.12. Understanding the Syllogism of Tendency

It is against this backdrop that the *syllogism of tendency* must be understood. The distinction between statistics and probability as tools for empirical sciences, and statistics and probability as self-standing disciplines, makes clear that a special internal method is needed for the latter. That method is precisely the syllogism of tendency.

The syllogism of tendency serves as the logical foundation upon which the entire theory of *Impossible Probability* is constructed. It is not merely another heuristic instrument among others; rather, it provides the structural reasoning by which probability and statistics can generate their own theoretical propositions, independent of empirical application. In this sense, the syllogism of tendency functions as the epistemological axis of Impossible Probability, organizing its logical development and ensuring that its formulations are rigorously deduced from valid premises.

30.13. Heuristic Methods Versus Internal Method

Thus, while the *Impact of the Defect*, the *Second Method*, and the *Effective Distribution* serve as heuristic methods that Impossible Probability offers to the empirical sciences for rational critique, the method used by Impossible Probability for its own internal development is different. That method is the syllogism of tendency.

It is through this logical mechanism that statistics and probability, as autonomous sciences, are able to develop, advance, and progress. The syllogism of tendency allows them to construct new forms of rational critique, not of other sciences, but of their own theoretical propositions. It makes possible the creation of novel concepts, definitions, and logical structures that can, in turn, be offered as heuristic instruments back to the empirical sciences. In this way, a dual movement occurs: statistics and probability

develop internally through the syllogism of tendency, while simultaneously contributing externally through heuristic methods to the rational critique of empirical reality.

30.14. Empirical Sciences and Formal Sciences

Consequently, the most important differentiation is not between quantitative and qualitative methods, nor between natural and social sciences. These distinctions, although common in the history of science, are ultimately superficial. The deeper epistemological division is between *empirical sciences*—whether natural or social—and *formal sciences*, namely logic and mathematics.

Within the family of formal sciences, one must recognize a diversity of disciplines, among them probability and statistics. Impossible Probability positions itself precisely here: as a scientific discipline within the formal sciences, one that constructs a new theory of statistics and probability. This theory is not derived from empirical testing but from the logical elaboration of its fundamental concept: the *empirical probability of a subject or option*. This is defined as the direct score or frequency of a subject or option relative to the total of all subjects or options within any given sample, regardless of the type of universe considered.

By grounding itself in this concept, Impossible Probability articulates itself as a formal science, developing universal theoretical propositions, while simultaneously offering heuristic methods that can be applied by empirical sciences in their pursuit of provisional hypotheses.

30.15. Universal Maxims in the Formal Sciences

Whereas empirical sciences—whether natural or social—are required to validate their hypotheses rationally only on a provisional basis, non-empirical or formal sciences operate under a different epistemological condition. Logic and mathematics, the analytic sciences, and within mathematics the *statistics of probability* or *Impossible Probability*, are sciences whose theoretical postulates do not derive from the testing of

hypotheses against empirical data. Instead, their postulates follow directly from the formal application of logic.

Whenever a proposition is formulated in accordance with correct logical procedure, the conclusion must necessarily be correct. The result is the production of conclusions or *maxims* that are genuinely universal in scope. In this sense, only in the formal sciences can one speak of an absolutely universal maxim, valid across any conceivable space-time continuum. This is the essential difference: while empirical sciences are always provisional, the formal sciences can aspire to timeless universality because their truths are grounded in the internal necessity of logic rather than the contingency of experience.

30.16. The Syllogism of Tendency as the Internal Method

In line with this distinction, the internal method used by *Impossible Probability* for the development of its own theoretical postulates has been the *syllogism of tendency*. This logical structure provides the discipline with the capacity to generate universal maxims, rooted in the necessary connections between premises and conclusions. Whereas empirical sciences rely on external testing and validation, Impossible Probability advances internally, by applying the syllogism of tendency to its fundamental concepts.

30.17. Definition of the Syllogism of Tendency

The *syllogism of tendency* is the method through which the *statistics of probability*, or *Impossible Probability*, derives its conclusions and establishes its universal maxims. In essence, the syllogism functions by extracting conclusions from logical premises. Provided that the premises are correct, and provided that no error occurs in the logical process of deduction from premise to conclusion, the conclusion must necessarily be true.

Consider, for instance, the case of classical statistics. Traditionally, descriptive statistics distinguishes between two types of tendencies: *central tendency* (mean, mode, median) and *dispersion tendency* (mean deviation, variance, standard

deviation). From these premises, it follows logically that the object of statistical study is the study of tendency itself. Furthermore, from these concepts of central and dispersion tendencies emerges the foundation upon which inferential statistics was later built. Thus, the syllogism of tendency demonstrates that the very core of statistics is the rational study of tendencies within data.

30.18. Two Types of Tendencies: Individual and Sample

Within Impossible Probability, a clear distinction must be made between two forms of tendency: **individual tendency** and **sample tendency**.

- *Individual tendency* refers to the characteristic form of behavior observed at the level of a single subject or option.
- *Sample tendency*, by contrast, refers to the aggregate pattern of behavior observed across the subjects or options comprising a sample.

By defining tendency in this way, Impossible Probability ensures that both micro-level (individual) and macro-level (sample) behaviors can be studied within a unified logical and statistical framework. This dual classification provides a more complete understanding of probability as it operates both at the level of single instances and collective patterns.

30.19. The Study of Reality and Events

Every syllogism that seeks to study the statistical behavior of reality—*what happens*—is, in Impossible Probability, a syllogism of tendency. This is because the theory begins from a rational definition of reality: reality is composed of phenomena, and phenomena consist of events. Since we cannot study reality "in itself," but only phenomena, the proper object of statistical analysis is the observable behavior of events in reality.

Events, however, can be defined in two ways. An event may be:

1. Something that occurs among different possible options (a probabilistic outcome), or

2. A subject within a sample (a particular observation among many).

From this, the logical conclusion follows: every event may be defined as a *subject or option*. This definition requires us to distinguish between two types of universes:

- *Universes of subjects or options* (infinite or population-based contexts).
- *Universes of limited options* (finite sets of possible outcomes).

Thus, the syllogism of tendency provides not only a method of logical reasoning but also a comprehensive epistemological framework for classifying the very objects of statistical inquiry.

30.20. The Concept of Empirical Probability

Since the object of statistics is the study of *tendencies*, and since tendency can be either individual or sample-based, the first step must always be the study of the *individual tendency*. This involves examining the behavior of a given subject or option, whether within universes of subjects or options (which may be infinite or population-based) or within universes of limited options.

In order to study individual tendency within the framework of *statistics of probability* or *Impossible Probability*, it is necessary to express it in statistical terms. At the individual level, this tendency is represented by the *direct value* or *frequency* of the subject or option. Logically, probability is defined as the ratio of the part to the whole. Therefore, the empirical probability of a subject or option is necessarily deduced to be equal to the direct value or frequency of that subject or option divided by the sum of all direct values or frequencies.

This fundamental statement of empirical probability is the starting point from which all subsequent formulations of Impossible Probability are derived. Yet even this basic definition rests upon a series of theoretical assumptions that must be explicitly recognized.

30.21. Derivation of the Concept of Empirical Probability

The definition of empirical probability—as the direct value or frequency of a subject or option divided by the sum of all direct values or frequencies across all subjects or options—emerges as a synthesis of two traditional notions.

First, in classical probability theory, the probability of an event was generally defined as the quotient of the frequency of that event divided by the total frequency of all events. Second, in classical statistics, it was commonly said that *relative frequency* is equal to the direct score divided by the total. Impossible Probability synthesizes these two concepts into a new and more general formulation: the *empirical probability of a subject or option* is equal to its direct score or frequency divided by the sum of all direct scores or frequencies of all subjects or options.

The consequences of this synthesis are profound. It means that in empirical sciences, *any collection of direct scores or frequencies* can now be studied in terms of statistical probability. The application of probability methods is no longer restricted to situations where only options are studied in the classical sense. From this point onward, beginning with the empirical probability of a subject or option, the *Second Method* of Impossible Probability can be applied to *any sample composed of direct scores or frequencies*.

Thus, whatever the nature of the empirical study, so long as it involves a sample containing measurable frequencies or direct scores, it can be subjected to rational critique by means of the Second Method. This is one of the principal reasons the approach is called the *Second Method*: alongside traditional methods, it represents a new and distinct way of studying and critiquing reality.

30.22. Symbolic Representation in Impossible Probability

In order to consolidate this synthesis, Impossible Probability introduces a symbolic framework. The *direct score* or *frequency* is represented by the symbol **xi**. The summation of all direct scores or frequencies is represented by **Σxi**. Finally, the number of subjects or options is represented by **N**.

This symbolic notation provides a concise language in which the concepts of empirical probability can be expressed and manipulated, allowing for logical deduction and theoretical development within the framework of Impossible Probability.

30.23. Theoretical Development Through the Syllogism of Tendency

From this foundation, the entire theoretical development of Impossible Probability unfolds as a chain of logical deductions, each one derived by applying the *syllogism of tendency* to the defined concepts. This method ensures that all new formulations remain grounded in logical necessity, providing the discipline with both internal coherence and universal validity.

30.24. Relationship Between Empirical Probability and Theoretical Probability

If empirical probability is defined as the ratio of direct score or frequency to the total, then the arithmetic mean of a set of empirical probabilities is calculated as the average of their summation. In symbolic terms, the mean of empirical probabilities is equal to the summation of all empirical probabilities divided by **N**, the number of subjects or options.

Since the sum of all empirical probabilities is equal to unity, and the mean is the summation divided by **N**, it follows that the arithmetic mean of empirical probabilities is equal to **1/N**. From this point forward, this ratio will be referred to as the *inverse of N*.

If the inverse of N is equal to the mean of all empirical probabilities, and if the inverse of N also represents the probability that each subject or option *should* have theoretically in a situation of perfect equality of opportunity by chance, then it follows that the inverse of N constitutes the *theoretical probability*.

30.25. Bias and Levels of Bias

If the difference between empirical probability and theoretical probability is understood as the *bias* by which a subject or option behaves differently from the behavior it should

theoretically display under pure chance, then this difference becomes the measure of bias. More precisely, the difference between empirical probability and theoretical probability corresponds to the *normal Level of Bias* of each subject or option, that is, the extent to which its observed behavior diverges from the expected theoretical behavior under conditions of equal probability.

The concept of bias thus plays a central role in Impossible Probability. It provides the formal mechanism by which deviations between reality and theoretical models are identified, measured, and rationally critiqued. This notion not only captures the departure from chance but also provides a rational structure for understanding inequality, irregularity, or non-random tendencies within any empirical distribution.

30.26. Extreme Probabilities and Possible Theoretical Biases

Because empirical probability is a statistic that must always lie between zero and one, it follows that the maximum empirical probability in a sample will be the largest probability observed among all subjects or options. The highest possible value to which this maximum probability can rise is one, which means that the *Maximum Empirical Probability Possible* is equal to unity.

Conversely, since empirical probability also cannot be less than zero, the minimum empirical probability in a sample is the lowest observed probability. The lowest possible value to which it can descend is zero, which means the *Minimum Empirical Probability Possible* is equal to zero.

From these bounds follow two important consequences for bias:

- If the *normal Level of Bias* is defined as the difference between empirical and theoretical probabilities, and if the maximum empirical probability tends toward its upper bound of one (the Maximum Empirical Probability Possible), then its bias tends toward the difference between one and the theoretical probability (the inverse of N). This difference—unity minus the inverse of N—defines the *Maximum Theoretical Bias Possible*.

- Conversely, if the minimum empirical probability tends toward zero (the Minimum Empirical Probability Possible), then its bias tends toward zero minus the theoretical probability, which, in absolute terms, is equal to the inverse of N. This establishes the *Maximum Negative Bias Possible*, which can never exceed the value of 1/N.

These formulations demonstrate that the logical structure of Impossible Probability is bounded both by absolute probabilities (zero and one) and by relative deviations from the theoretical distribution (maximum positive and maximum negative biases).

30.27. Studies of Equality and Bias

If theoretical probability is given by the inverse of N (1/N), and this represents the probability that each subject or option should theoretically possess in a condition of equal opportunity under chance, then the ideal of equality can be defined. In a study designed to test for equality of opportunities, the goal is for every empirical probability to converge toward its theoretical probability, such that each subject's normal Level of Bias approaches zero.

Research of this kind—where the objective is to validate whether opportunities are equally distributed across a sample—will be called *studies of equality*. These studies serve to evaluate the extent to which empirical distributions approximate the ideal of fairness or equal opportunity, and they do so by examining how closely empirical probabilities align with their theoretical baseline of 1/N.

30.28. Studies of Positive Bias

Consider a set **N**, such as in a multiple-choice test where, among all items, only one answer is correct. Out of the entire N, there is only one *ideal subject or option*. In this case, the rational expectation is that the empirical probability of the ideal option should approach the maximum observed probability in the sample. As that maximum empirical probability tends toward unity, its Level of Bias should simultaneously tend toward the *Maximum Theoretical Bias Possible*.

Such studies, where the purpose is to examine whether a particular subject or option rises above the others to reflect an ideal or privileged outcome, are called *studies of positive bias*. They test for situations where one option is expected—and ideally observed—to dominate all others, thereby reflecting the alignment between theoretical expectation (the existence of a unique correct answer or ideal) and empirical confirmation (the concentration of probability on that subject).

30.29. Studies of Negative Bias

In some cases, the logical ideal for a given subject or option within a sample is not to approach the maximum probability, but rather the minimum. When the empirical probability of a subject tends toward the *Minimum Empirical Probability Possible*, and thus toward the *Maximum Negative Bias Possible*, such research contexts are designated as *studies of negative bias*.

The rational evaluation of these studies requires clear criteria. For example:

- In a study of *equality of opportunities*, the ideal is for every subject's empirical probability to converge toward its theoretical probability, 1/N. The closer the empirical probabilities are to their theoretical baselines, the greater the tendency toward equality. Rational acceptance of equality will only occur if the difference between each empirical probability and its theoretical probability is less than or equal to a given margin of error, known as the *Validity of Equality*. Alternatively, it may be expressed as the requirement that the difference between the Maximum Theoretical Bias Possible and the normal Level of Bias is greater than or equal to a given margin of reliability, called the *Significance of Equality*.
- In a *study of positive bias*, where the ideal is for the maximum empirical probability to converge toward the Maximum Theoretical Bias Possible, rational acceptance occurs only if the difference between these values is less than or equal to a margin of error, called the *Significance of Positive Bias*, or if the normal

Level of Bias is greater than or equal to a reliability threshold, the *Validity of Equality*.

- In a *study of negative bias*, the expectation is that the subject or option under examination will tend toward the Maximum Negative Bias Possible. The smaller the difference between this maximum negative bias and the observed Level of Bias, the stronger the rational justification for accepting the result. Acceptance requires that this difference remain within an error margin (the *Significance of Negative Bias*), or alternatively, that the observed Level of Bias meets or exceeds the threshold of reliability defined as the *Validity of Negative Bias*.

In each case, the rational critique of hypotheses depends upon establishing quantitative thresholds—margins of error and margins of reliability—that define whether the empirical distribution sufficiently embodies the ideal condition (equality, positive bias, or negative bias).

30.30. The Relationship Between Bias and Dispersion

Bias and dispersion are intimately related in statistical reasoning. As bias increases in a sample, so too does dispersion. Specifically, the greater the tendency of the maximum probability in the sample to approach the *Maximum Empirical Probability Possible* (equal to unity), the greater the overall dispersion of the sample becomes.

Because the sum of all empirical probabilities must equal one, as the maximum probability tends toward unity, all other probabilities necessarily tend toward zero—the Minimum Empirical Probability Possible. This leads to a widening gap between the maximum and the rest of the distribution, thereby increasing dispersion.

Thus, the stronger the convergence of the maximum toward unity, and the stronger the convergence of the remaining subjects or options toward zero, the greater the sample dispersion will be. In this scenario, bias levels reach their theoretical extremes: the Level of Bias for the maximum approaches the *Maximum Theoretical Bias Possible* (1 – 1/N), while the Level of Bias for the remaining options approaches the *Maximum Negative Bias Possible* (–1/N).

From this, it follows that the *Maximum Theoretical Mean Deviation*, the *Maximum Theoretical Variance*, and the *Maximum Theoretical Standard Deviation* are only possible when these two conditions are simultaneously met:

1. The bias of the maximum is equal to the Maximum Theoretical Bias Possible.
2. The bias of all other subjects or options is equal to the Maximum Negative Bias Possible.

In such a case, the Maximum Theoretical Mean Deviation can be formally expressed as the average of the sum of the Maximum Theoretical Bias plus the product of the Maximum Negative Bias multiplied by (N – 1). This simplifies to the average of twice the Maximum Theoretical Bias.

Similarly, the Maximum Theoretical Variance is given by the average of the square of the Maximum Theoretical Bias plus the square of the inverse of N multiplied by (N – 1). Finally, the *Maximum Theoretical Standard Deviation* is equal to the square root of this Maximum Theoretical Variance.

Through these formulations, Impossible Probability connects the concepts of bias, dispersion, and statistical variability into a single logical structure, showing that dispersion is not an independent phenomenon but the necessary consequence of biases within the distribution.

30.31. Deviations and Maximum Theoretical Measures

If the *Intermediate Deviation* is defined as half the difference between the maximum and minimum values, then in the extreme case where the maximum empirical probability is equal to one and the minimum is equal to zero, the *Maximum Possible Theoretical Intermediate Deviation* must necessarily equal 0.5.

Similarly, the *Maximum Theoretical Mean Deviation* between the maximum and minimum values can only be obtained by dividing by two the absolute difference between the *Maximum Theoretical Bias Possible* and the *Maximum Negative Bias Possible*. These formulations demonstrate that the measures of dispersion, when

considered in their theoretical limits, are themselves subject to logical necessity and can be formally derived from the extreme behaviors of bias and probability.

30.32. The Syllogism of Tendency as the Foundation of All Formulation

The *syllogism of tendency* is the method that, within *Impossible Probability*, has enabled the development of all its formulations. Whether applied to *normal* or *omega models*, it provides the rational critique necessary for analyzing differential relations between empirical and theoretical statistics, as well as ratio-based relations such as critical proportions (explained in Section 11 of *Introduction to Impossible Probability*).

In synthesis, the syllogism of tendency underlies every logical proposition and mathematical formulation within this theory. It is the structural principle that ensures consistency, rigor, and systematic development, making it not merely a methodological tool but the epistemological backbone of the entire framework.

30.33. Methodological Tools for the Empirical Sciences

In practical terms, the *Second Method*, along with the *Impact of the Defect* and the *Effective Distribution*, function as methodological instruments for the rational critique of empirical reality. These tools may be employed in any empirical science, whether social or natural.

However, internally—within the formal development of statistics of probability or *Impossible Probability*—the method used to construct formulations is exclusively the syllogism of tendency. By chaining together syllogisms grounded in fundamental premises, the theory has generated new conclusions, definitions, and concepts. These, in turn, have given rise to novel mathematical and statistical structures capable of providing more refined instruments for the rational critique of reality.

30.34. The Provisional Nature of Empirical Science

Both the social and natural sciences, insofar as they are empirical, must employ identical methods when studying reality. Yet, these methods must always preserve a margin of rational doubt, or *empirical skepticism*. This margin is nothing other than the rational critique of all theoretical formulations, since in empirical science nothing can be considered universal except provisionally.

No empirical hypothesis can remain rational beyond a sufficient or infinite span of time, for in such a horizon the possibility of refutation always exists. This condition of provisionality is not a weakness of science but its defining strength: it ensures that knowledge remains open to correction and continuous refinement.

30.35. The Evolution of Critical Rationalism

Critical rationalism, whether in the version of Kant—who, through the antinomies of pure reason, already recognized that some hypotheses, though logically structured, lacked empirical demonstration—or in the falsificationism of Popper, or even in the formulation of Impossible Probability, has always aspired to the Kantian moral imperative of establishing universal maxims. Ideally, these would take the form of laws like those of Newton, universally valid across all time.

Yet, in practice, as long as we only can attain provisional knowledge, the dream of Hegel's *absolute idea* remains unattainable for the empirical sciences. It may be realizable, at best, in non-empirical or formal sciences. The greatest virtue of the evolution of Enlightenment rationalism up to the present has been the recognition of the absolute necessity of science for human progress. The open question that remains is whether humanity will ever succeed in achieving an empirical formulation that can claim true universality [this is a good question for the future Superintelligence and the global AI, will they able to attain eternal truths?].

30.36. Kantian Classification: Synthetic and Analytic Sciences

At this stage, the distinction between *quantitative natural sciences* and *qualitative social sciences* proves epistemologically unfounded. The more logical classification—one with clear Kantian resonances—is the distinction between *synthetic sciences* and *analytic sciences*.

- The *synthetic sciences* are the empirical sciences, encompassing both natural and social domains. [First section in each hemisphere in the matrix in GAI]
- The *analytic sciences* are logic and mathematics. [the foundation of Real Intelligence, the second section in the matrix in GAI should be founded in logics and maths]

Within mathematics, one must identify distinct disciplines, among which stand statistics and probability. For the development of statistics of probability—or *Impossible Probability*—the method proposed is the *syllogism of tendency*. This method provides the epistemological foundation for building and advancing the theory of probability and statistics as a formal science in its own right.

30.37. Conclusion: The Function of the Syllogism of Tendency

The *syllogism of tendency* is, in its essence, a method for deducing logical and rational conclusions about tendencies within statistical probability. By working from logically valid premises, it enables the formulation of conclusions that are not contingent but necessary.

Through the chaining of premises and conclusions, the syllogism of tendency allows for the construction of a fully developed statistical theory of probability. This theory, in turn, generates new methods of inquiry that can be applied to the rational critique of empirical sciences. In this way, the syllogism of tendency operates simultaneously as a formal foundation for Impossible Probability and as a methodological bridge connecting formal science with empirical application.

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Rubén García Pedraza
imposiblenever@gmail.com